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Research Article

Policy Design for COVID-19: Worldwide Evidence on the Efficacies of Early Mask Mandates and Other Policy Interventions

Abstract: *To understand the extent to which a policy instrument's early adoption is crucial in crisis management, we leverage unique worldwide data that record the daily evolution of policy mandate adoptions and COVID-19 infection and mortality rates. The analysis shows that the mask mandate is consistently associated with lower infection rates in the short term, and its early adoption boosts the long-term efficacy. By contrast, the other five policy instruments—domestic lockdowns, international travel bans, mass gathering bans, and restaurant and school closures—show weaker efficacy. Governments prepared for a public health crisis with stronger resilience or capacity and those with stronger collectivist cultures were quicker to adopt nationwide mask mandates. From a policy design perspective, policymakers must avoid overreacting with less effective instruments and underreacting with more effective ones during uncertain times, especially when interventions differ in efficacy and cost.*

Evidence for Practice

- Despite its higher efficacy in containing the coronavirus disease 2019 (COVID-19) spread, the mask mandate was the least frequently utilized among six commonly used mandates during the first global wave of the pandemic, and most governments adopted it later than others.
- The mask mandate is consistently associated with lower infection and mortality rates in the short term. Early adoption of mask-wearing mandates is also consistently associated with lower COVID-19 infection rates in the long term, indicating the link between a government's intervention speed and policy instrument efficacy.
- By contrast, domestic lockdowns and restaurant closures do not show any consistent relationships in the short term. Mass gathering bans and school closures need more time to manifest their efficacies as short-run policy instruments. Early adoption of these mandates, however, does not maintain their efficacy in the long run.
- Governments prepared for a public health crisis with stronger resilience or capacity and those with stronger collectivist cultures were quicker to adopt nationwide mask mandates.
- Policymakers must be aware of various policy instruments' differential efficacies and their preferred timing to achieve public health goals. Each instrument's benefits and costs must be gauged against the expected effects and timeframes.

Before the widespread availability of effective vaccines, the only viable approach to slow the spread of SARS-CoV-2 (COVID-19) has been to use government-imposed non-pharmaceutical mandates such as social distancing, mandatory mask-wearing, mass gathering bans, stay-at-home orders, and closures of schools and businesses. Studies have assessed the efficacies of individual mandates (e.g., Betsch et al. 2020; Cheng et al. 2020; Dehning et al. 2020; Ferguson et al. 2020; IHME COVID-19 Forecasting Team 2021; Schlosser et al. 2020; Xu et al. 2020). Despite their demonstrated effectiveness, many government mandates hurt the economy and other aspects of social and personal wellbeing (Gourinchas et al. 2020; McKibbin and Fernando 2020; Spelta et al. 2020; see also Gaynor and Wilson 2020; Martin-Howard and Farmbry 2020; Menifield and Clark 2021; Yancy 2020 about social and racial equity concerns).

A growing body of scholarship has studied how these mandates compare in relative efficacies (e.g., Anderson et al. 2020; Chernozhukov, Kasahara, and Schrimpf 2021; Haug et al. 2020; Haushofer and Metcalf 2020). Yet, little is known about whether *early* adoption of policy mandates makes a difference in crisis management. To our knowledge thus far, only a small body of studies has examined how policy intervention timing shapes differential effects on COVID-19 containment. Using simulation models,

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for instance, Pei, Kandula, and Shaman (2020) show that if the United States adopted social distancing policies and other restrictive mobility measures one to two weeks earlier than they did during the pandemic's early phase (March 15 to May 3, 2020), they could have avoided substantial cases and deaths. Other research (e.g., Alagoz et al. 2020; Amuedo-Dorantes, Kaushal, and Muchow 2020; Lai et al. 2020; Tian et al. 2021) reports similar findings from different single countries. While previous studies underscore the importance of intervention timing they did not question, which policy instruments should have been adopted earlier than others, how early the action should have been taken, and whether the evidence can be generalized globally. An exception is Zheng, Li, and Sun (2021), who question the importance of early policy action using global data (152 countries), but the study does not compare the relative efficacies of different policy instruments, particularly on the benefits of early intervention.

Suppose the mask-wearing mandate is more effective than other measures in both the short- and long-run. If it is imposed shortly after the initial outbreak, it may be unnecessary to mandate more drastic measures such as domestic lockdowns and business closures (Haug et al. 2020). However, as we will demonstrate, many governments chose the reverse strategy during the first global wave of the pandemic due to a lack of scientific knowledge, guidelines from international and national health institutions, and different cultural and behavioral orientations, among other factors.

Medical research has shown that transmission rates among asymptomatic and pre-symptomatic groups may be as significant as those among symptomatic patients (Lee et al. 2020; Savvides and Siegel 2020). Moreover, COVID-19 transmission rates vary across age groups (Davies et al. 2020). For example, epidemiological data and simulation models indicate lower transmissibility among children than adults. If so, early school closures alone may have less effect in controlling infection spread (Viner et al. 2020) than other restrictive measures targeting adults (Davies et al. 2020). While these factors complicate government strategies for virus containment, early adoption may still be crucial for a mandate to attain most gains.

However, without conducting a randomized controlled trial, it is highly difficult to compare different government mandates' efficacies (Haushofer and Metcalf 2020). Given the inherent challenges in launching randomized experiments (e.g., Abaluck et al. 2021), is it feasible to design an observational study with existing data on worldwide mandate adoptions to gauge their relative efficacies? Our research addresses this critical policy and management question by asking which government mandate likely benefits the most from early adoption. Our focus on early adoption relates to the disaster and crisis management literature's emphasis on early preparedness, adaptability, and learning systems (e.g., Boin et al. 2016; Comfort, Boin, and Demchak 2010; Kapucu 2008; Perry, Lindell, and Tierney 2001; Van Wart and Kapucu 2011). It also relates to the public administration literature's concept of government agility, which partly highlights how fast actions enable governments to address problems arising from uncertain and rapidly changing environments (Ansell, Trondal, and Øgård 2017; DeSeve 2020; Janssen and Van Der Voort 2016; Mergel, Ganapati, and Whitford 2020; Moon 2020; Room 2011; Walker, Rahman, and Cave 2011; also see McCann, Selsky, and Lee 2009 for an application to private sector organizations). Governments' initial mistakes can be corrected by adaptive responses, but they could still face insurmountable barriers in managing the crisis down the road. While our research design does not allow us to study the adaptive process (e.g., Janssen and Van Der Voort 2016; Walker, Rahman, and Cave 2011), we can still examine if early adoption makes any difference in government policy outcomes.

To understand the extent to which a policy mandate's early adoption is crucial, we leverage unique worldwide data that record the daily evolution of policy mandate adoptions and COVID-19 infection and mortality rates from January 1 to July 15, 2020, a timeframe generally considered the first wave of the global pandemic (Cacciapaglia, Cot, and Sannino 2020). Specifically, we identify policy mandate adoption timing and compare the relative efficacies between early, late, and noninterventions by using both cross-sectional and longitudinal research design. Our analytic focus is the associations between COVID-19 infection rates (and mortality rates) and six mandates commonly adopted across the globe and their short- and long-run efficacies. A post-hoc analysis will also examine what pre-existing governance, institutional, and cultural factors explain countries' early adoption of the most efficacious mandate.

The analysis reveals that domestic lockdowns and restaurant closures do not display any consistent associations with new infection and mortality rates in the short term. Mass gathering bans and school closures need more time to manifest their short-term efficacies. By contrast, mask mandates exhibit the strongest and most immediate associations with lower new infection and mortality rates in the short run. More importantly, both cross-sectional and longitudinal analyses provide consistent evidence that only mask mandates demonstrate persistent long-run efficacy from early adoption.

Our post-hoc analysis of the antecedents of early mask mandate adoption further indicates that the temporal adoption of the mask mandate was not randomly taken across countries. Governments prepared for a public health crisis with stronger resilience or capacity—as measured by hospital beds per population—were quicker to adopt nationwide mask mandates. Moreover, governments with stronger collectivist cultures were quicker to adopt mask mandates.

In the remainder of the paper, we first present how the policy design literature helps explain the global patterns of initial mandate adoptions, followed by some vignette cases illustrating the success of speedy government responses to COVID-19. We then present our empirical strategy and data. Results with various modeling approaches and alternative measurement for both focal independent and dependent variables are presented. We conclude with the implications for both practice and scholarship.

Pandemic Responses from a Policy Design Perspective

The unprecedented pandemic provides a unique setting to examine how uncertainty shapes government behavior on policy instrument choices. The policy design literature argues that policymakers consider various tradeoffs between resource-intensiveness (e.g., administrative costs and operational simplicity), targeting (e.g., precision and selectivity), political risks (e.g., public support or opposition), coerciveness/intrusiveness (e.g., restrictions placed on the target population's autonomy or liberty), and other constraints such as ideological principles and cultural receptiveness (An and Tang 2020; Dahl and Linbolm 1992; Hood 1986; Kelman 1981; Linder and Peters 1989; Salamon 1981). For instance, while all mandates infringe on personal liberty, governments often prefer more coercive ones if their implementation demands fewer administrative resources (Dahl and Lindblom 1992; Hood 1986). Besides, precision and selectivity matter because less targeted instruments are more likely to face stronger political opposition, despite requiring greater administrative costs (Salamon 1981).

Other factors, such as bureaucratic politics, powerful veto players, and interest groups that are often beyond the design calculus (cf. Knott and Miller 1987; Moe 1995) can disrupt the effectiveness of instruments. But as Howlett (2019) writes, "most policy design theory operates under the assumption that governments will attempt to act as efficient policy-makers, or at least wish to do so as a normative goal, if not one always achieved in practice." The assumption of policymakers knowing how to act or adjust efficiently does not hold when they face tremendous uncertainties on the relative efficacies of various policy instruments (Churchman 1967; Rittel and Webber 1973). In such uncertain and wicked situations, policymakers are inclined to choose instruments that are more stringent and coercive (to reduce administrative costs), more short-term and targeted (to reduce political opposition), and more ideologically and culturally receptive (to increase public compliance). As a result, a government can unintentionally err in choosing either insufficient or excessive policy instruments (Howlett 2019; Howlett and Kemmerling 2017; Jones, Thomas III, and Wolfe 2014; Maor, 2012, 2014). Maor (2012) calls such a phenomenon "policy overreaction" or "disproportionate policy response," which occurs when political executives are overconfident, placing too much faith in their intuitions on the effectiveness of certain policies over their costs. If sustained, those overreactions can further grow as policy bubbles (Jones, Thomas III, and Wolfe 2014; Maor 2014). Under limited resources and attention, the government's overreaction with some instruments can lead to underreaction on others, especially when policymakers have to choose with uncertainty (Howlett 2019).

Although a government may adjust the policy mixes subsequently, it must still forgo potential gains that could have been achieved by acting early with an optimal policy mix. As our analysis shows later, this angle explains the global pattern of government mandates during the pandemic's early phase.

Switching to the analytic perspective, without knowing which mandate is more effective *ex-ante*, our empirical focus is governments' early adoption of each policy instrument and the relative efficacies of different instruments. As Moon (2020) has argued, South Korea's early success in containing the virus's spread was possible thanks to the government's agile approach. From a global perspective, a vital element of crisis management is understanding the extent to which a policy mandate's early adoption is crucial for its success while minimizing the public's cost.

Vietnam is an illustrative case of speedy mandate adoption. By mid-January 2020, despite an absence of COVID-19 cases in the country, Vietnam issued the first guidelines about the virus. Following the first two cases at the end of January, the Vietnamese government adopted most containment measures, for example, school closures and international travel restrictions, weeks before the World Health Organization declared COVID-19 as a global pandemic (Van Tan 2021). Similar approaches were taken by other East Asian countries or territories such as Hong Kong, Macau, and Mongolia. In comparison with neighboring countries—for example, Cambodia—Vietnam adopted most measures weeks in advance and recorded much fewer per-capita cases (Hoang et al. 2020). Despite being a highly centralized political system, Vietnam also adopted a more localized approach to controlling the pandemic, with adaptive partial lockdowns after local outbreaks.

A similar approach can be found in Australia, which privileged a localized approach with collaborative national coordination (Downey and Myers 2020; Moloney and Moloney 2020). The country temporarily introduced partial restrictions at the State and Territory levels following a logical path tied to declining infection rates. Restrictions were adopted at the pandemic's beginning, at the same time as in Europe, despite significantly fewer infection cases. Australia's mitigation strategy was successful, recording fewer cases and deaths than many comparable countries in the OECD (Organisation for Economic Co-operation and Development) (Child et al. 2020). By contrast, many European countries such as France and Italy failed in initial mitigation, and as a result, they gradually switched from a soft to a hard approach. After missing the golden opportunity to act early, most European countries subsequently adopted stricter measures than Australia and Vietnam but still experienced much higher death rates.

These examples show that different countries adopted various mandates as part of an overall national strategy for coping with COVID-19. From a global, comparative perspective, it is likely that (1) various mandates differ in their short and long-time efficacies, and (2) for the most effective mandates, early adoption can shape the eventual success of the overall design. In the following section, we present the data and methods to test these two propositions.

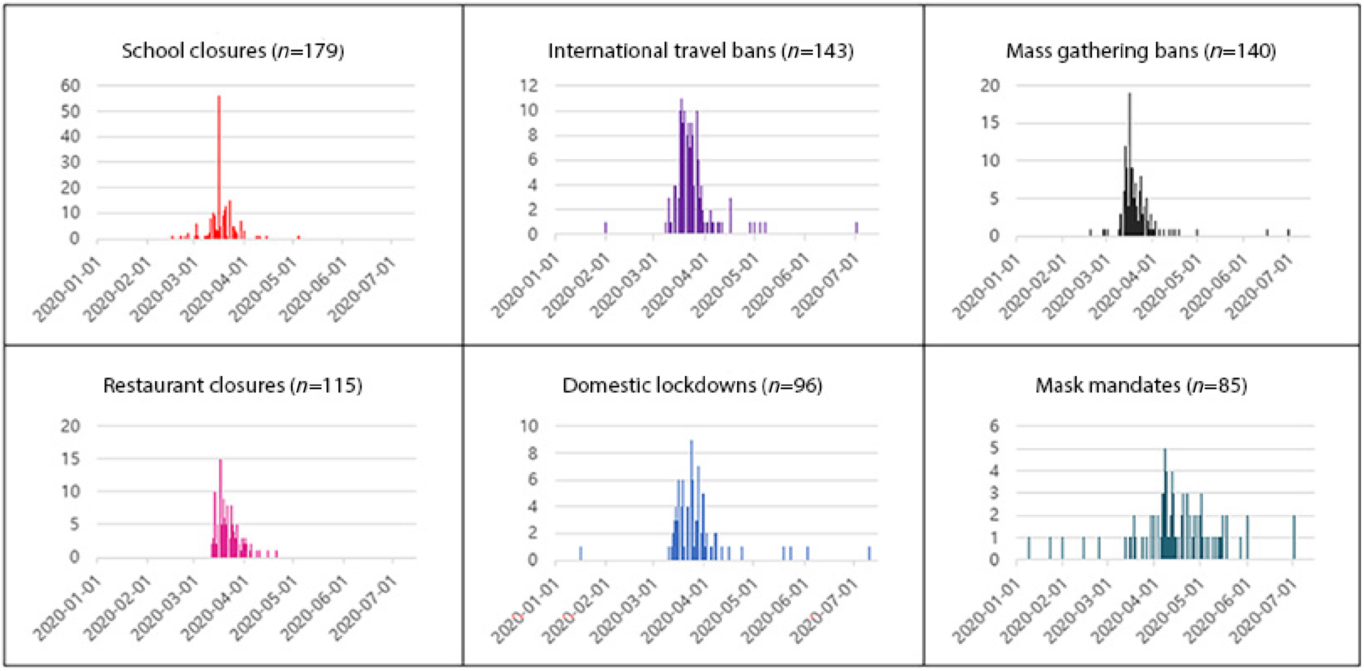
Data and Methods

Descriptive Statistics

Data on mandates are obtained from the Response2covid19 dataset (Porcher 2020). The dataset manually records daily evolution of COVID-19 mandates, starting from January 1 to July 15, 2020 for nearly all countries in the world. Unless the information was missing from the raw data sources, countries were included, allowing the current study to capture up to 188 nations.[1]

Figure 1 visualizes the number of countries undertaking the first nationwide adoption of each mandate over time. Compared to the other interventions, governments generally took mask mandates later. The adoption distribution, however, exhibits varied densities, indicating substantial heterogeneity across countries; some countries took the mask mandates relatively early while others followed suit later.

Figure 2 presents the worldwide data on the number of days taken after the first reported case for each policy instrument's adoption as a strict, nationwide mandate. This measures the relative speed of mandate adoptions, considering the differential timing the



Notes: The figure presents the frequency of adoption of each mandate at the national scale (strict) by *n* countries. The scales of the y-axis are all different.

Figure 1 Worldwide Adoptions by Mandate Type Over Time

Notes: The days for all mandates were calculated based on the mean day of all measures implemented in each country. *n* represents the number of countries. Box length indicates an interquartile range. The bar inside the box represents the median. Small bars outside the box indicate 1.5 times interquartile range from the first and third quartiles.

Figure 2 Number of Days Taken for Strict Mandate Adoptions Worldwide

virus arrived in each country. The bar represents the median number of days taken. As indicated by the interquartile range boxes, there is also substantial heterogeneity across nations for each strict, nationwide mandate. When the median is taken as the baseline, countries generally mandated school closures first and mask mandates last. When considering the six mandates together, the global median adoption time is 14 days. We thus define *early* mandate adoption for all six measures as being taken within 14 days after the first reported infection in each country. Interestingly, the mask mandate was the least frequently utilized among the six mandates during the first global wave of the pandemic.

Overview of Empirical Approach

We first measure the short-term efficacy of six policy mandates on new infection rates. Considering that nonpharmaceutical mandates often have no immediate effects due to the virus's incubation period, we consider different timeframes: 5, 9, 12, 21, and 30 days. The first timeframe—between 5 and 12 days—is selected because most patients experience symptoms during this period (Lauer et al. 2020). Hence, for policymakers, 12 days would be the most important lag to gauge short-run policy efficacy. The other timeframes, 21 and 30 days, are used to see if the mandate shows more lasting results.

In this estimation, we use country fixed-effects regressions to take advantage of the panel data structure (country-day). This approach has key merits for our observational study. First, many countries are inherently different from each other, making the validity of cross-sectional analysis questionable. Instead, longitudinal analysis with the fixed-effects model allows a country itself to serve as a counterfactual to its changes while holding constant all time-invariant country-specific features, including each country's tendency to under-report infection cases. It has been documented that reporting biases vary across countries due to systematic differences in both testing capacity and transparency (Li et al. 2020; Rahmandad, Lim, and Sterman 2020). The fixed-effects model controls for these systematic variations. The same applies to variations in death reporting tendencies; hence, we also examine mortality rates for all analyses as an alternative measurement.

Both outcome metrics have pros and cons. A significant advantage of using infection rates as a policy outcome is its direct relevance to COVID-19; infections are direct virus outcomes. By contrast, reported deaths are not necessarily direct consequences of COVID-19 because they can result from a combination of COVID-19 and comorbidities. Still, the mortality rate metric could be a more accurate proxy for the virus spread since it has less to do with countries' differential testing capacities and transparency propensities associated with under-(or over-) reporting. Regardless, both measures are subject to systematic bias across countries. Thus, we rely on our research design to control for these country-specific propensities.

Yet, we acknowledge that some countries might have improved their testing regime over time and become more effective in detecting infection cases and virus-induced death tolls. To the extent, such learning effects are present in some countries rather than others, our research design cannot fully address systematic reporting biases. Given the difficulty of precisely measuring the *true* levels of COVID-19 specific infection and mortality and their changes over time, we explore both outcomes and compare different policy instruments' efficacies between the two metrics.[2]

After analyzing the immediate influence of policy instruments, we examine the persistence of their efficacy by extending the time horizon. Specifically, we focus on early adoptions and compare their results to those of late and nonadoptions. For this analysis of long-run influence, our empirical approach unfolds in two ways. First, we compare countries using cross-sectional data and least-squares regressions. This exercise is to establish a baseline regarding the presence and importance of early mandate adoption *between* countries. The primary dependent variable here is the log of the averaged total infection rate between the 90th and 120th day after the first reported infection in each country. Alternatively, we also examine the log of the averaged mortality rate during the same period.

A cross-sectional analysis only focuses on differences between countries. As a result, it does not tell us how COVID-19 infection and death rates would have been different in a given country had it adopted a policy mandate earlier than later. To capture the dynamic nature of the relationships, namely, how policy adoption relates to infection and mortality rates over time, we turn to panel data using within-country variations (i.e., country fixed-effects). Given the panel data structure, we model each adoption (early and late) to capture *a shock at only one point in time*, that is, the date the mandate came into effect nationally, while allowing the dependent variables "cumulative infection rates and mortality rates" to evolve daily for all data points. The model attempts to purge the pure variations in both early and late mandate adoption timing,[3] using the variations within countries while taking into account differences in their inherent capacities for implementing the instruments.

All models are estimated with robust standard errors clustered at the subcontinent level, which is at a greater geographical scale than a country, to avoid potential downward biases in standard error estimation (Cameron and Miller 2015). The rationale is that the error terms may not be utterly independent of other neighboring countries in the same subcontinent, given research findings that virus transmission and policy diffusion are more significant among neighboring countries (Mistur, Givens, and Matisoff 2020; Sebhatu et al. 2020). This subcontinent-level clustering generates more conservative standard errors than country-level clustering while still allowing for considerable degrees of freedom.[4]

Variables

COVID-19 Cases, Deaths, and New Rates. Data on cases and deaths come from the Johns Hopkins Coronavirus Resource Center. The data have been published daily since January 1, 2020. The data allow us to compute the cumulative cases and deaths daily. To compare across countries of different population sizes, we adjust cases per million inhabitants or total cumulative cases per million inhabitants to build our primary dependent variable and total cumulative deaths per million as an alternative dependent variable.

In analyzing mandates' short-term efficacy, we account for the real trend of new cases and fewer cases reported during weekends by measuring the mean of cases per million inhabitants reported in the last seven days. For a given day *d* and a country *c*, the number of new cases per million inhabitants is thus computed as $\text{NewCases}_{c,d} = \frac{1}{7}\sum_{l=0}^{6} Cases_c$ with *l* the number of lags and *Cases* the reported cases per million inhabitants. We apply the same smoothing procedure for total cases. We use these smoothed variables to compute the new case rate as $\text{RateNewCases}_{d,c} = \frac{NewCases_{d,c}}{TotalCases_{d,c}} \times 100$. This new case rate is a good proxy for the short-term pandemic scale and is used as a dependent variable.

For the outcome metric in the long-term analysis, we examine total cumulative cases per million inhabitants, which are good proxies for government capacity to contain the pandemic during a period. In the cross-sectional model, we use the log of averaged total cases per million between the 90th and 120th days after the first reported case as the dependent variable; this controls for the differences in pandemic trends across countries, capturing most countries in the data. The variable thus allows us to compare countries within the same time interval.

Policy Mandates and Adoption Timing. Using the Response2covid19 dataset (Porcher 2020), we consider six mandates that have been adopted to contain the virus spread: mask mandates, international travel restrictions, domestic lockdowns, mass gathering bans, restaurant closures, and school closures. Mask mandates are obligations to wear masks in public spaces. International travel restrictions are bans on international flights or border closures, except for cargo flights or repatriation. Domestic lockdowns are stay-at-home orders. Mass gathering bans refer to limitations on public or private gatherings. Restaurant and school closures refer to these facilities' closures.

The mandates are coded in a three-scale format. They can be mandated for the entire population ("strict" intervention), for only a subpopulation ("partial" intervention), for example, in a localized area or for a given category of the population, or not implemented at all. This differentiation is essential because strict mandates will be useless in some cases, for example, if the virus is contained in a given region. The categorization allows us to compare different clusters of countries—being strict versus being partial in implementing mandates versus not implementing. Policy mandates are coded 0 if not implemented, 0.5 if partially implemented, and 1 if strictly implemented.

In the long-term analysis, we focus on mandate adoption timing as an essential factor in virus containment (Ferguson et al. 2020; Pei, Kandula, and Shaman 2020). To operationalize this, we include dummies capturing whether a country implemented a given mandate early on. As mentioned above, we define *early* adoption as having the mandate in place within 14 days after the first reported case, as this is the global median for all six policy instruments (see Figure 2).

Some might wonder how exactly we utilize the variations in mandate adoption timing across the six policy instruments since countries could have taken these mandates quite simultaneously, as suggested by Figure 1. Tables B1–B3 present the correlation matrixes for all focal independent variables (i.e., different mandate adoptions) and control variables with cross-sectional and longitudinal datasets, respectively. Across countries (Table B1), some measures such as *early* international travel bans and mass gathering bans were often introduced with other mandates like school closures and restaurant closures at similar times ($0.59 \leq r \leq 0.69$). Still, their adoptions were not always taken at the same time. Thus, our estimation allows us to tap into these variations. With the longitudinal data, we can further use daily variations in mandate adoption timing across the six policy instruments. As illustrated by Table B2 (all strict adoptions) and B3 (all early adoptions of strict measures), here the collinearity concern is effectively minimized. In other words, the daily change records in all mandate adoptions afford us sufficient variations to tease out the mandates' respective associations with infection and mortality rates over time. This is also the case with the threshold for early action set at the first 14 days.

Control Variables. In the short-term analysis, we use various controls to capture the pandemic's dynamics. Some controls are standard in SIR (Susceptible, Infected, and Recovered) epidemiological models. For example, we account for (1) the cumulative total cases and (2) deaths reported at date d in a given country c. We also add two extra controls to improve model estimation as they indicate where a country stands at a particular time during the pandemic: (3) the lagged value of the dependent variable, which is the new case rate and (4) the logged number of days since January 1, 2020, a time trend accounting for the timing of the virus's worldwide spread, which could be a proxy for the importance of knowledge and experience in containing the virus.

In the long-term analysis with country-level cross-sectional data, we add controls measuring whether countries ever adopted each policy mandate during the analysis period to differentiate their early adoption from their mere presence; this purges the variations in early mandate adoptions from those of their mere presence. We then include different groups of socio-economic and institutional variables from the World Bank. Following recent studies (Bouckaert et al. 2020, Holman et al. 2020, Khan et al. 2020, Liang et al. 2020, Tartof et al. 2020), we include two variables capturing national healthcare capacities or resilience—(1) hospital beds per 1,000 inhabitants and (2) health expenditures as a percentage of GDP in 2017. We also use three controls capturing the population's health risk—(3) the percentage of the population with diabetes, (4) the percentage being overweighed, and (5) the median age of the population (Dowd et al. 2020). Note that the last variable is correlated strongly with percentage of the older population aged 65 or more, with $r = 0.920$ in our main estimation reported in Figure 4.[5]

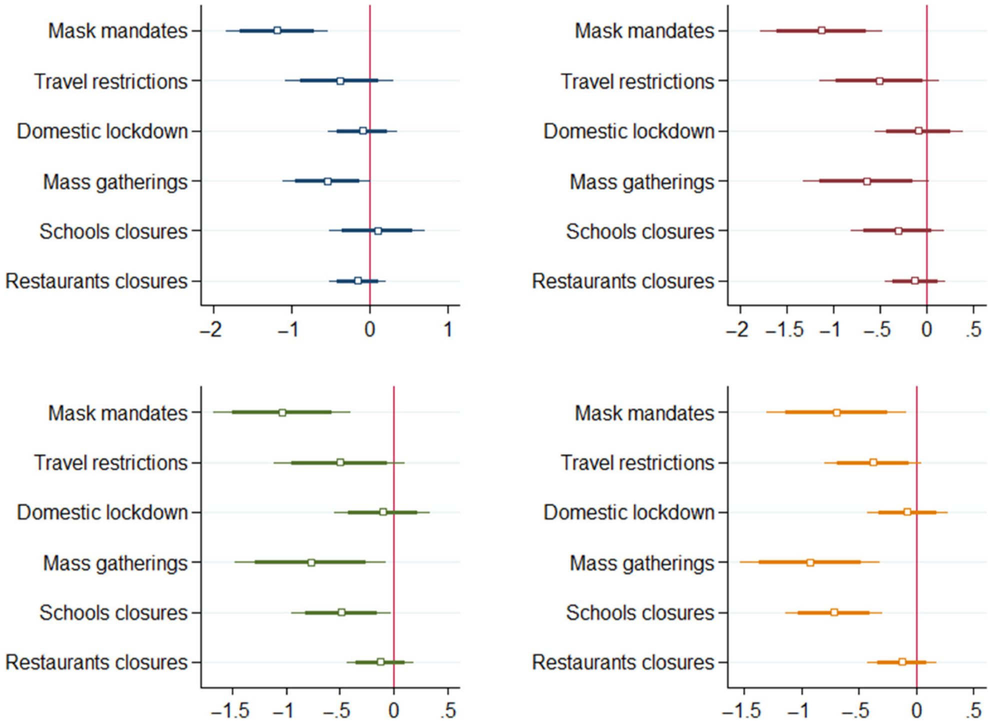
Further, to consider a country's developmental level, we add two controls: (6) Gross domestic product (GDP) per capita and (7) government effectiveness score. Prior pandemic experience (Capano et al. 2020) and COVID-19 testing capacity could also shape a country's response outcomes. We thus include (8) past mortality rates jointly counted from SARS (severe acute respiratory syndrome), H1N1, and Ebola, and (9) averaged cumulative COVID-19 tests per million during the same period used for the dependent variable (i.e., between 90th and 120th day after the first reported case). Finally, we include (10) five continents fixed-effects to account for similar unobservable characteristics that neighboring countries often share. Note that all these 10 groups of control variables are absorbed by the country fixed-effects for the long-term analysis with panel data.

Results

Short-Term Efficacy of Policy Mandate Adoption

Figure 3 reports the associations between strict policy mandates and new infection rates 5, 9, 12, and 21 days after their adoptions, using country fixed-effects models. The full results, including 30 days lags, are reported in Table A1. It should be noted that any changes in countries' mandate adoptions during the study period are captured by the focal independent variables. In other words, if a government lifted a particular mandate and re-imposed it later, those changes are reflected in the model.

With this operationalization in mind, three significant findings are worth noting. First, only two mandates show consistently significant relationships over all time lags between 5 and 21 days: mask mandates and mass gathering bans. Specifically, the coefficient for mask mandates shows the greatest magnitude until 12 days, suggesting it as the most efficacious and appropriate instrument for policymakers targeting short-run outcomes. The result is quite consistent with earlier research that specifically measured the mask mandate's short-term effect (Lyu and Wehby 2020). Similarly, international travel bans show some efficacy but at a later time lag



Notes: This table summarizes the associations between policy mandates and the rate of new cases after controlling for other variables. Full results are reported in Table A1. n = 21,126–21,155 country-day pairs, covering 164 countries in all models. Fixed-effects regression for panel data used for estimation. Robust standard errors clustered by subcontinents. Within R-squared is between 0.86 and 0.87. 95% (bold) and 99% (thin) confidence intervals are reported around the coefficient.

Figure 3 Short-Term Efficacy of Mandate Adoption on New Case Rates

and in smaller magnitudes than those of mask mandates and mass gathering bans.

Second, domestic lockdowns and restaurant closures do not seem to help contain virus transmission in the short term, showing no significant relationship until 30 days. Lastly, while mask mandates' efficacy appears immediately and then decreases monotonically over time as one might expect, mass gathering bans and school closures show otherwise; their influence seemingly needs more time to materialize. These results are still consistent with previous research that found relatively higher efficacy of both measures (Haug et al. 2020).

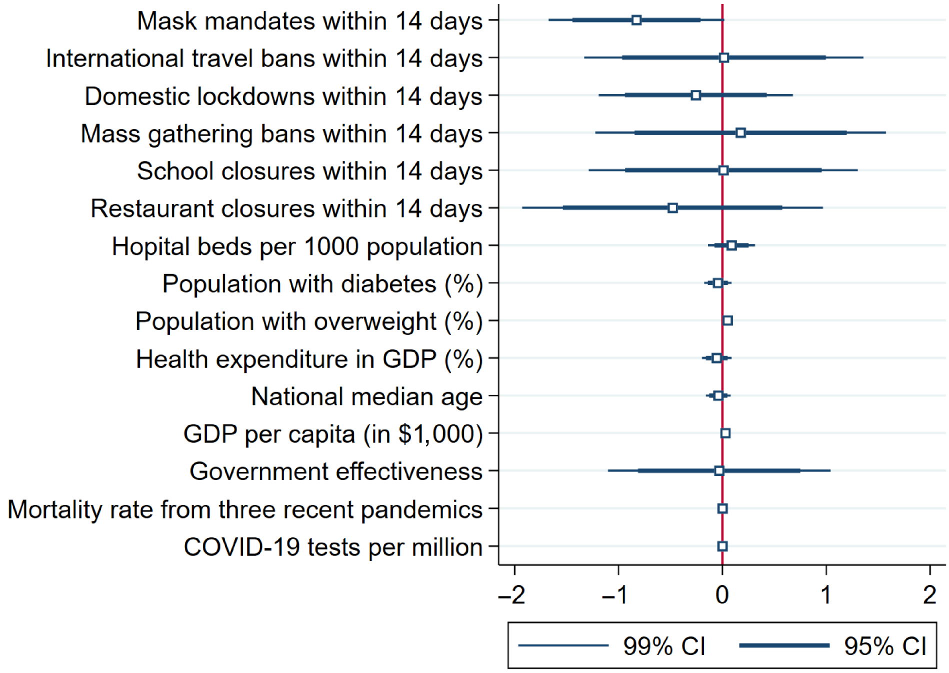
Table A2 reports the results of a similar model with dummies for the different mandate scales (strict, partial, or not adopted). Different from Figure 3, in which the implementation scale takes three different values, the model uses dummies instead to differentiate the effects of partial versus strict measures. Consistent with the results in Figure 3, mask mandates—both strict and partial—show the strongest association with lower new case rates until 12 days, again suggesting them as the most efficacious policy instrument for short-run goals.

Control variables show the expected results in all models of Table A1 (i.e., Figure 3) and A2. Cumulative deaths per million inhabitants are negatively correlated with new case rates. More cumulated deaths decrease the potential for contamination. The lagged value of the new case rate is positively correlated with the one observed in t. Finally, the time trend has a negative sign on new case rates. This likely indicates that knowledge and experience in handling the virus decrease new case rates. Note that the policy mandates might also be correlated with the controls, particularly total deaths and total cases resulting from the mandates' past implementation. The value of these variables might already capture some associations with existing orders. In this sense, the different policy mandates' coefficients might thus be downward biased in both analyses.

We repeat the two preceding analyses using mortality rates as an alternative dependent variable, namely new death rates. The results, reported in Tables A3 and A4 support the main findings on the immediate role of mask mandate adoption: the new death rate is consistently negatively associated with mask mandates until 12 days after the adoption, and they show the largest magnitude compared to the other five instruments (Table A3). This finding also holds when the mask mandate is differentiated by strict versus partial implementation (Table A4). Again, strict measures show consistent associations with lower mortality rates until 12 days after their adoptions.

Long-Run Efficacy of Early Mandate Adoption: Cross-Sectional Analysis

We now turn to the long-run efficacies of different mandates with an emphasis on early adoption. Figure 4 shows that countries mandating mask-wearing within two weeks of the first COVID-19 infection had lower rates of total infections (measured in log) in later days (between the 90th and 120th day) than those that did not. Interestingly, among six policy instruments, only the mask mandate retains strong significance in the association with total infection rates in later days. The size of the early mask mandate coefficient in Figure 4 is substantial as its one-unit increase translates to a 0.45 standard deviation of lower infection rate in the



Notes: N = 129 countries. Estimates represent the predicted infection rate change between the 90th and 120th days (log of total infections per million) by one unit increase of the variables. Each mandate was coded in three scales: 0 (no adoption), 0.5 (partial/regional adoption), and 1 (strict/nationwide adoption). Whether they were ever mandated during the study period was controlled but not shown here. Five continents-fixed effects are also included but not reported here. Robust standard errors clustered by 19 subcontinents. R-squared is 0.64 and adjusted R-squared is 0.56. For full results, see Table A5.

Figure 4 Long-Run Efficacy of Early Mandate Adoption (Cross-Sectional Analysis)

129 sample countries. With each policy mandate coded as 0 (no adoption), 0.5 (partial/regional), and 1 (strict/national), the model suggests that countries with mask mandates within the first two weeks saw a 0.90 standard deviation decrease in the infection rate than those with no such mask mandates.

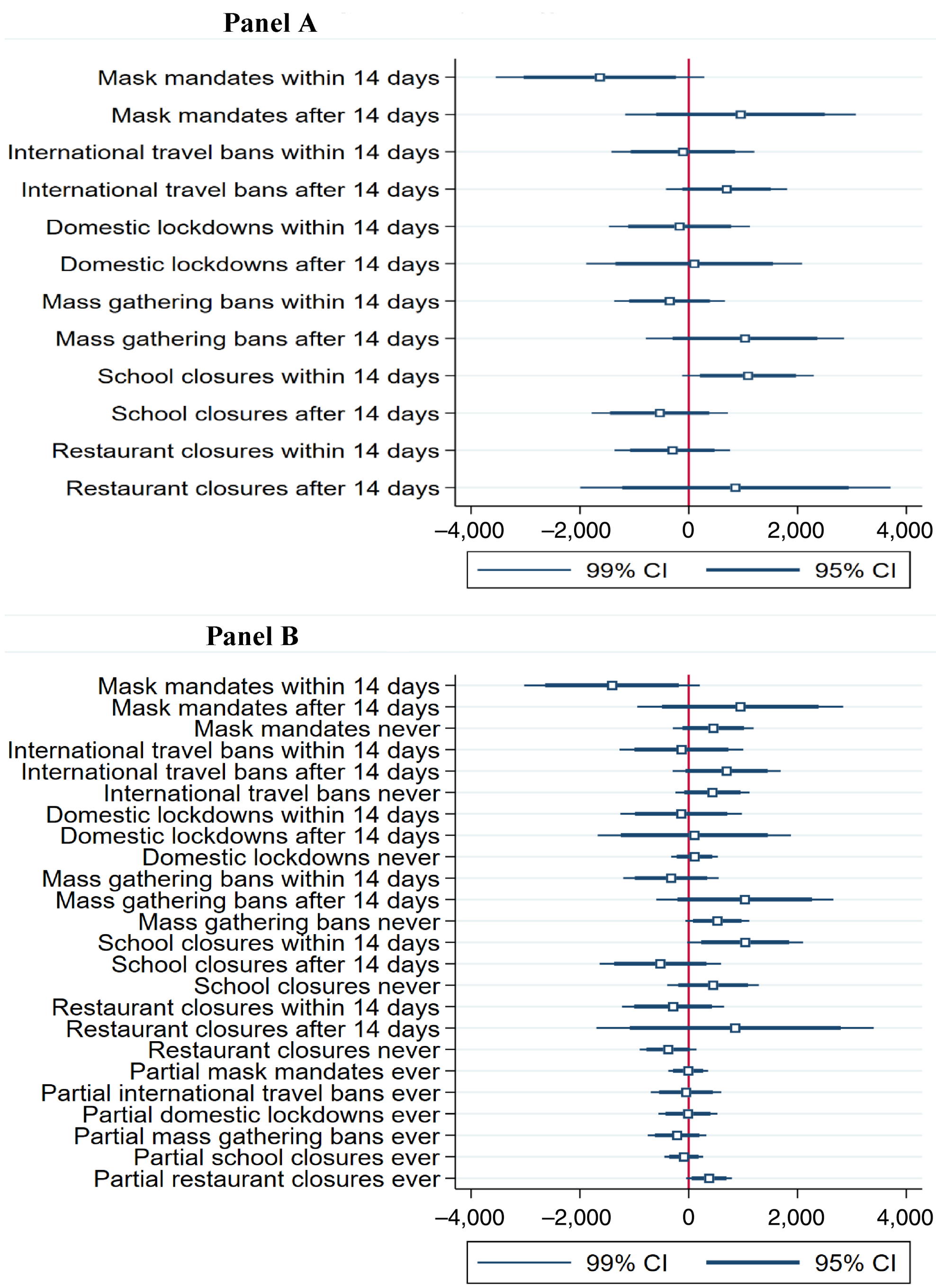
Most controls are not statistically distinguishable from zero, except for the following three variables: (1) the percentage of the overweighed population shows a strong positive association as expected, (2) GDP per capita is also significantly correlated with the logged infection rate; the positive sign likely reflects significant infections among the advanced economies in Europe and North America, compared to less-developed nations in other continents, and (3) tests done per million shows a positive relationship, indicating that countries with higher testing capacity detected more infections.

We also ran the model in a stepwise fashion with each control variable group to examine if collinearity drove the key results among the variables. This exercise, reported in Table A5 with full results and point estimates, assures that collinearity is not a concern. We also repeated all models without taking a log on the dependent variable; the results remained the same. Next, we repeated the preceding analysis with the alternative outcome variable, mortality rate. These results in Table A6 also show the robust associations for early mask mandate adoption. In particular, compared to the other five policy instruments, the results strongly reaffirm the distinct role of mask mandates for consistently lower associations with mortality rates.

Long-Run Efficacy of Early Mandate Adoption: Panel Analysis

We next use panel data to examine the dynamic nature of the relationships between government responses and disease control over time. The model compares the long-term associations between early mask mandates and infection rates to those from the other five policy instruments among three groups of countries: (1) nations implementing a strict mandate early on (i.e., early adopters), (2) those implementing a strict mandate after the first two weeks (i.e., late adopters), and (3) those implementing no strict mandate at all during the entire study period (i.e., non-adopters). Capturing *a shock at only one point in time*, namely the date the mandates came into effect nationally, the analysis estimates the long-term infection associations with both early and late mandates relative to their absence, zeroing particularly on the potential importance of early actions.

Figure 5 presents the results from the fixed-effects model as the main specification (upper panel) and the results from the random-effects model (lower panel) as a supplementary specification (also see Table A7 for the full results of both models with exact point estimates). The fixed-effects model accounts for all unobservable time-invariant confounders without requiring the stringent assumptions of the random-effects model.[6] Yet the latter's main advantage is that it can estimate the coefficients for variables that do not have any within-country variation, namely the no-mandate groups and partial mandates ever group (also see note 3). In any event, regardless of the model choice, the panel data analysis is consistent with the earlier cross-sectional results, showing that countries with an early nationwide mask mandate saw a significantly lower infection rate over time than those without such an order during the first global wave, on average, by as many as 1,410 or 1,634 per million population ($p < .05$).[7] These effect sizes are also substantial as they translate to 0.60 and 0.70 standard deviation decreases in total infection rates among the 164 countries in the sample.



Notes: n = 24,684 country-day pairs, covering 164 countries in both panels. Fixed-effects (within) regression used for panel A. Random-effects generalized least squares regression used for panel B. Robust standard errors clustered by subcontinents in both panels. Within R-squared is 0.18 for the fixed-effects model and overall R-squared is 0.16 for random-effects model. The results with exact point estimates are reported in Table A7.

Figure 5 Long-Run Efficacy of Early Mandate Adoption (Panel Data Analysis). Panel A: country fixed effects model, Panel B: country random effects model

These results of nationwide mask mandates also hold when the model further considers the dynamic nature of partial/regional mandates, namely capturing the day each partial/regional measure was put in place (nationwide mask mandates within 14 days: $\beta = -1{,}363$, $p = .05$ for fixed-effects model and $\beta = -1{,}185$, $p = .048$ for random-effects model).[8] Taken together, the consistent associations from both fixed-effects and random-effects models provide supporting evidence for the persistence of early mask mandates in controlling virus transmission over time.

The random-effects model also shows that, except for school closures, the coefficients for all early mandates are consistently negative, signaling the potential importance of early intervention. Other than mask mandates and school closures, however, none of them is statistically significant. In fact, nationwide early school closures are *positively* associated with higher total infection rates in subsequent days ($p < .05$) in both random- and fixed-effects models, casting doubts on its long-run efficacy. This contrasts with its short-term results documented earlier. The random-effects model also suggests that countries that did not nationally mandate mass gathering bans (i.e., non-adoption group) saw significantly higher total infection rates—525 infections per million ($p < .05$).

Next, we re-ran both models with mortality rates. These results are reported in Table A8. It shows that early mask mandate adoption shows a negative sign as expected. Late mask mandate adoption also shows a weak negative relationship. However, the early adoption's significance is far from the conventional level, suggesting that the model does not afford enough statistical power. As to why the longitudinal model results hold with infection rates but not with mortality rates, more research will be needed to understand this nuanced finding. Moreover, interestingly, in both models, domestic lockdowns show a positive association with mortality rates, casting doubts on its long-term efficacy. Combined with short-run efficacy results, domestic lockdowns may not just be less effective instruments in the short term; their early adoption may also bring about unintended negative consequences in the long run. Future research should examine the underlying factors that can explain these dynamic results.

Post-Hoc Test: Analyzing the Antecedents of Early Mask Mandate Adoption

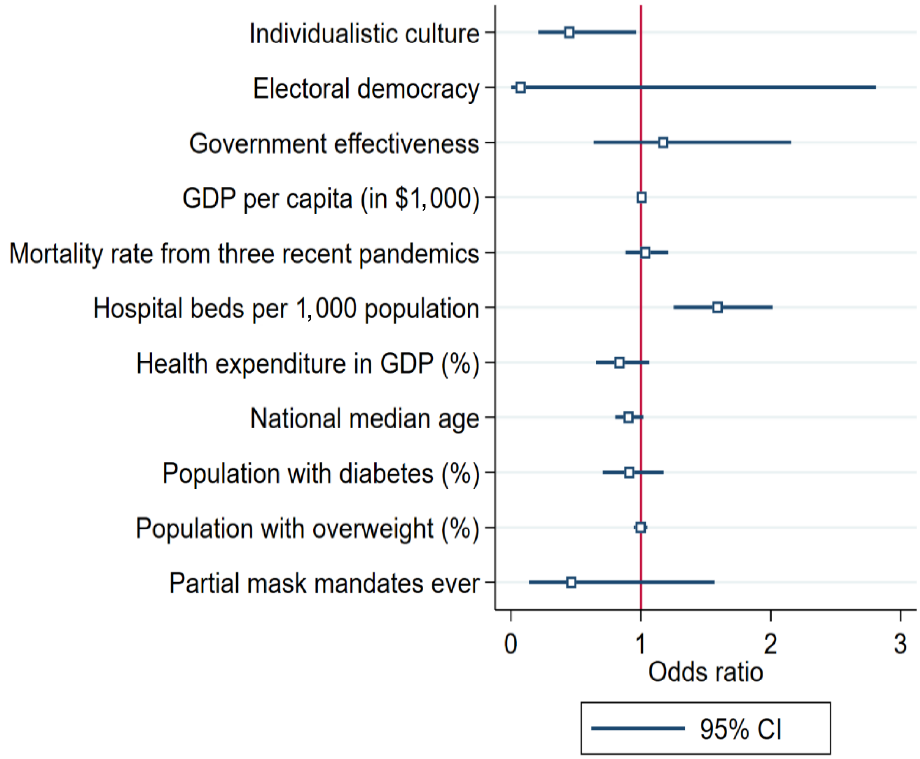
Readers may be curious about the antecedents of early mask mandate adoption across countries. The primary purpose of this study is not to answer this question. Instead, we sought to evaluate the relative efficacies of various policy instruments designed to subdue COVID-19 virus progression. The study focused on early mandate adoption in this context and found the mask mandate to be the most efficacious among the others, both immediately and in the long run. Beyond this focus, as a post-hoc test, we present below preliminary analysis on some possible determinants of such early policy interventions, particularly mask mandates.

We fully acknowledge the limitations of this post-hoc model, which does not consider time-varying factors (e.g., the scientific community's improved understanding of the virus over time) that rapidly evolved and simultaneously affected policymaking during the early pandemic waves. Instead, our analytic focus here examines several pre-existing country-level factors—national healthcare capacities, population's health risk, developmental level, prior pandemic experience, and partial mandate adoption ever (see Figure 4). In addition, given the recent empirical finding of how democratic institutions shape non-pharmaceutical intervention (NPI) adoptions (Sebhatu et al. 2020) and the viewpoint on their connection to state capacity in dealing with a crisis (Puppim de Oliveira and Berman 2021; cf. Fukuyama 2020), the model includes an electoral democracy score (Lindberg et al. 2014). Lastly, a growing body of research underscores the critical role of culture in shaping the quality of government and public management (An and Tang 2020; Persson, Parker, and Widmalm 2017; Porcher 2021; Stivers 2021; Van der Wal, van den Berg, and Haque 2021; also see Johansen 2019, for social equity context) and how the cultural orientation captured by the "collectivism–individualism" continuum (Hofstede 1980) influences governments' overall COVID-19 policy intervention speed (Chen et al. 2021) and individuals' receptivity to the mask mandate, in particular (Lu, Jin, and English 2021). The model, therefore, includes each country's collectivism–individualism orientation score, which may be the most relevant cultural factor in the mask-wearing context.

For the modeling approach, we use a cross-sectional research design with ordered logistic regression. For the outcome measure on early national mask mandates, instead of focusing on a narrow time interval of "14 days" and likely limited variations derived from such binary measurements, we cast a wider net with a quartile-based ordinal coding to fully capture cross-country variations in adoption timing. Countries that never enacted nationwide mask mandates during the study period are coded 0, while those in the last quartile in the distribution of days taken for the national mandate adoption are coded 1, and so forth until countries in the first quartile of the distribution are coded 4.[9]

As reported in Figure 6, the results show that most variables—electoral democracy, government effectiveness, prior pandemic experience, and general public health risk factors—do not meaningfully predict the pace of nationwide mask mandate adoption. The two most significant predictors are collectivist culture and the number of hospital beds per population. Countries with a stronger individualist culture were less likely to adopt strict mask mandates earlier. Specifically, when we rank order countries by individualism cultural score to focus on the top 20 percentile in the data distribution, many of them are found in Europe and North America, including Luxembourg, Iceland, Switzerland, Ireland, Sweden, Belgium, Italy, Netherlands, United Kingdom, and United States. These countries have a stronger individualist culture, and they did not mandate nationwide mask-wearing regulations during the study period. Not coincidentally, their infection rates were much higher than the world average, at least one standard deviation above.[10] On the other hand, those with a stronger collectivist culture were quicker to adopt nationwide mask-wearing mandates. A group of these countries can noticeably be found from the bottom 20 percentile of individualism cultural score (i.e., top 20 percentile for collectivism score) in our analysis, and they are located in other parts of the world, including South Korea, China, Vietnam, Thailand, and Indonesia in Asia, Venezuela in South America, and Burkina Faso and Mozambique in Africa. These nations adopted mask mandates earlier than most western countries, and their later infection rates were all below the world average.

In addition, the number of hospital beds strongly predicts the likelihood of speedier mask mandate adoption. Considering that the model also controls for various demographic risk factors and health expenditures in GDP (a reasonable proxy for investment in healthcare) and that the overwhelming load on the health system was a key policy concern during the peak of virus infections and fatalities, the number of hospital beds represents resilience or capacity for handling the COVID-19 public health crisis (Sebhatu et al. 2020).[11] Ironically, countries with stronger resilience or capacity to cope with the unprecedented crisis were keener to quickly adopt the least costly preventive measure (Comfort, Boin, and Demchak 2010; cf. Capano et al. 2020; also see Bel, Gasulla, and Mazaira-Font 2021). However, further descriptive analysis revealed that, unlike the cultural variable, countries with more beds (or fewer beds) are not necessarily those with a lower infection rate (or a higher infection rate), except for some Asian countries, including South Korea, Japan, Mongolia, and Timor-Leste. In fact, in our sample, South Korea and Japan stand as the top two countries in the number of hospital beds per population,



Notes: *N* = 89 countries. The sample size is smaller than the previous cross-country analysis because Hofstede's individualistic culture variable is available for fewer countries. The dependent variable is quartile-based ordinal coding from the distribution on days taken for mask mandate adoption at the national level, coded 0 (no adoption), 1 (fourth quartile), 2, (third quartile), 3 (second quartile), and 4 (first quartile). The results of individualistic culture and hospital beds remain robust when only these two variables are included as regressors. The results also remain in place for a bivariate relationship for both variables. Five continents-fixed effects included but not reported here. Robust standard errors clustered by 19 subcontinents. Pseudo R-squared is 0.18 for the reported model. Coefficients and 95% confidence intervals reported in odds ratio.

Figure 6 Predictors of Early Mask Mandate Adoption (Ordered Logistic Regression)

and they also show lower infection rates than the rest of the world.[12]

Discussion and Conclusions

When reviewing the literature on disaster preparedness and responses about 20 years ago, Perry, Lindell, and Tierney (2001) diagnosed that very little research existed on how government policies influence preparedness and response activities. They also noted that most empirical research had been about the United States, and comparative studies mainly took a case study approach. This assessment on disaster management research has virtually remained the same until today (Aldrich 2020). However, the emergency of the COVID-19 pandemic at the global scale has created opportunities for a breakthrough, especially with respect to comparative empirical research.

With COVID-19 hitting nearly every country globally, public administration researchers can examine how and why governments worldwide have differed in their responses to the crisis (Baldwin 2021; Boin, McConell, and Hart 2021). A majority of earlier studies took a case study approach to answer this question (e.g., An and Tang 2020; Bouckaert et al. 2020; Capano et al. 2020; Comfort et al. 2020; Downey and Myers 2020; Ramírez de la Cruz et al. 2020; Turrini, Cristofoli, and Valotti 2020; Weng et al. 2020; Yan et al. 2020). Yet, with various COVID-19 databases growing worldwide, more comparative research can be undertaken with quantitative approaches (George et al. 2020). Our study addresses this need by comparing governments' early adoptions of various nonpharmaceutical mandates as crisis management and policy tools.

As the pandemic is characterized by many uncertain and risk factors, governments' agile actions are essential (e.g., Bel, Gasulla, and Mazaira-Font 2021; DeSeve 2020; Mergel, Ganapati, and Whitford 2020; Moon 2020; Van Dooren and Noordegraaf 2020; Walker, Rahman, and Cave 2011). Among various agility aspects (Mergel, Ganapati, and Whitford 2020)—for example, decision-making speed, bottom-up procedure, adaptability, responsiveness, transparency, and accountability—this study focuses on the speed of governments' policy mandate adoption and their relative efficacies. Using worldwide data tracking the daily progression of the virus and government mandate adoptions during the first wave of the pandemic (January 1 to July 15, 2020), we have analyzed both short- and long-term associations between the six commonly adopted mandates and virus infection and mortality rates. With different modeling approaches and alternative measurements (for both the focal independent and dependent variables), the analysis shows that domestic lockdowns and restaurant closures do not display any consistent associations with new infection and mortality rates in the short term. Mass gathering bans and school closures need more time to manifest their short-term efficacies. By contrast, mask mandates exhibit the strongest and most immediate associations with lower new infection and mortality rates in the short run. More importantly, both cross-sectional and longitudinal analyses provide consistent evidence that only mask mandates demonstrate persistent long-run efficacy from the early adoption.

In light of these findings, it is surprising that many governments in the world appear to have not picked the most efficacious set of policy instruments against the virus. As shown in Figures 1 and 2, the mask mandate was the least frequently adopted policy instrument among the six. Temporarily, many governments were significantly late in adopting the mask mandate, compared to other instruments, suggesting inadequate speed in their responses. These findings beg the question of how the world would have looked differently had more governments taken the reverse strategy—mandating mask-wearing regulation early on, along with mass gathering bans and school closures, instead of relying on more socially and economically costly, yet less effective measures such as domestic lockdowns and restaurant closures. The insufficiency in instrument choice and speed can be partly explained by a lack of scientific understanding about the virus itself and differentiated effects of various policy instruments during the early phase of the pandemic. For instance, during the early stage of the pandemic, international organizations such as the World Health Organization and domestic health authorities such as the US Center for Disease Control dismissed the importance of mask-wearing as a precautionary measure. By following their lead, many governments wasted precious time in combating the virus's spread with mask mandates.

The insufficiency can also be partly explained by the long-standing policy design literature positing that, in the face of significant uncertainties around both the policy problem itself and relevant instrument effectiveness, policymakers must manage various tradeoffs between resource-intensiveness, political risks, and the public's compliance. As such, they tend to choose measures that are (1) more stringent and coercive, (2) more short-run and targeted, and (3) ideologically and culturally more receptive. While our post-hoc analysis of the antecedents of early mask mandate adoption cannot capture these nuances in the initial instrument choice process, it reveals that government effectiveness and electoral democracy do not explain time variations in mask mandate adoption during these uncertain times. Still, the temporal adoption of the mask mandate was not taken randomly across countries. Governments prepared for a public health crisis with stronger resilience or capacity—as measured by hospital beds per population—were quicker to adopt nationwide mask mandates. Moreover, governments with stronger collectivist cultures were quicker to adopt mask mandates.

The latter finding sheds light on the critical role culture plays in crisis management specifically and public management more generally. The role of culture has been long neglected by public administration scholars. Instead, leadership, managerial style, science-based evidence, and formal institutions have been treated as more prominent contributors to public performance and management quality. Yet, recent studies have started to deepen our knowledge of the role of national culture in comparative public administration. For instance, Porcher's (2021) empirical analysis shows that culture is a significant constituent factor in government quality across the globe. Comparing East Asian polities' early COVID-19 responses against developed Western countries', An and Tang (2020) further highlight how the interaction between national culture and government's policy instrument choice affects its endurability and effectiveness. Adding to these trends, our analysis calls for attention from comparative researchers to the broader role of cultural orientations in shaping policy and management outcomes across nations.

Focusing on the pandemic's early phase, our study has implications for future policy choices as well. At the time this research was conducted, most countries were still at least several months away from providing vaccines to large portions of their population. Moreover, many countries have been unexpectedly experiencing the spread of COVID-19 variants. Hence, the nonpharmaceutical policy mandates we studied are still the primary weapons for fighting against the COVID-19 and its variants. With the world still experiencing the epidemic, citizens in many countries have questioned the relative efficacies of various policy instruments because of their adverse economic and social impacts. Anecdotal evidence and laboratory experiments have shown the effectiveness of mask-wearing in reducing infection and death rates (Betsch et al. 2020; Leung et al. 2020; Peeples 2020; Xu et al. 2020). But the importance of the mandates' early adoption and their short and long-term efficacies relative to each other have not been examined in most observational studies. Our research fills this gap by showing that different mandates may not be equally effective in managing the pandemic (Also see Haug et al. 2020). Policymakers must be aware of various policy instruments' differential efficacies and their preferred timing to achieve public health goals. In the current turbulent times, governments play a central role, and each instrument's benefits and costs should be gauged against the expected effects and timeframe.

We offer a few caveats to the interpretation of our findings. Our results do not imply that governments should abandon some policy mandates. The estimated correlations are additive associations while controlling for other factors; they should be read in relative terms, not absolute ones. Hence, it would be misleading to interpret nonsignificant correlations as an indication of a policy mandate showing no efficacy at all. For example, domestic lockdowns, as shown in other recent studies (Haug et al. 2020), may have a limited effect on COVID-19 containment. Meanwhile, early evidence from a smaller number of countries suggests that domestic lockdowns are the most effective instrument (Dehning et al. 2020; Flaxman et al. 2020; Schlosser et al. 2020). Our results, however, indicate that the additive efficacy of domestic lockdowns, apparently the most socially costly policy instrument, can be limited, particularly when all other mandates are already in place.

In addition, this study does not estimate the optimal time for early mandate adoption. The 14-day early adoption window was chosen as a result of data distribution analysis. The virus, however, reached various countries at different times. Hence, the definition of early adoption must be adjusted based on each country's unique circumstances. Next, while our data collection allows us to control each mandate's implementation scale (i.e., partial/regional vs. strict/national), it does not allow us to control whether the population respects mandate compliance and how governments enforce each mandate. The current analysis could be complemented by future research using mobility data (e.g., Badr et al. 2020; Kraemer et al. 2020; Mehari 2020; Porcher and Renault 2021) or implementation records from various government units (e.g., Gupta et al. 2020; White and Hébert-Dufresne 2020). Scholars may also link individual-level surveys to contextual data to examine how institutions, cultures, and regulations interact to influence citizens' willingness and attitudes toward mandate compliance (Alesina and Giuliano 2015; An and Tang 2020; Bouckaert et al. 2020; Dai et al. 2020; Gelfand et al. 2011; Lu, Jin, and English 2021; Pedersen and Favero 2020; Porcher 2021) and how public administrators can facilitate those compliances (Schuster et al. 2020).

Current research analyzes the common responses of governments over a short period during the early pandemic phase, in which measures were taken to slow the spread of the virus and avoid overwhelming intensive care units. Some governments, however, took different strategies, such as rapid natural herd immunity. Swedish health authorities, for example, predicted that the exponential increase of contaminations in urban areas would allow the population to rapidly acquire the antibodies and attain herd immunity before May, 2020. In the period studied in this research, however, Swedish authorities failed in their strategic planning, with infection rates three times higher than neighboring countries like Denmark or Norway, which followed a suppression strategy similar to other countries with immediate domestic lockdowns, longer international travel restrictions, and stricter school closures than Sweden. Other countries, like Israel, pursued herd immunity via a rapid and wide-scale vaccination campaign with longer time horizons. Further studies could compare the efficacies of various vaccination policies, other nonpharmaceutical interventions, and varying timeframes.

Lastly, it is also important to note that our model did not examine the adaptive character of government responses (e.g., Janssen and Van Der Voort 2016; Walker, Rahman, and Cave 2011). Instead, we looked at governments' early actions for all six mandates while considering the different times when the virus reached each country (i.e., the day of the first reported infection). With the pandemic lasting for more than a year, many governments lifted and re-imposed mandates repeatedly. At the same time, scientific evidence and deeper learning about the virus and policy tools have been accumulated. While earlier research has studied what country characteristics explain emulation of their neighboring peers' policy adoptions (Mistur, Givens and Matisoff 2020; Sebhatu et al. 2020), and whether earlier hard measures put in other similar countries predict a focal country's initial intervention speed for its own stringent policies (Bel, Gasulla, and Mazaira-Font 2021), no empirical studies have specifically examined how learning shapes governments' adaptation of their policy choice and design over time to rapidly changing environments (for a case study approach, see Christensen and Lægreid 2020, Moloney and Moloney 2020, and Moon 2020 among others). For instance, to what extent and how did governments learn from other successful countries? Conversely, to what extent and how did they learn from their own trials and errors since the start of the pandemic? These questions will complement current research to broaden our understanding of the role of government agility in crisis management.

As the COVID-19 pandemic persists with the emergence of virus variants, policymakers and researchers must assess, which policy instruments and strategies prove most effective and how best to speed up the learning curve. It is crucial to identify the most effective policy instruments and learn fast enough to determine, which measures to embrace and abandon.

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Data Availability
All final data used in the empirical analyses and the replication codes are available to download from the following open repository site: https://www.openicpsr.org/openicpsr/project/149421/version/V1/view.

Notes
1. The version used in the paper is the V5 covering the first wave of COVID-19 and is accessible on Open ICPSR: https://www.openicpsr.org/openicpsr/project/119061/version/V5/view.
2. We also considered reproduction rates (R0). We obtained the data from the London School of Hygiene and Tropical Medicine (https://epiforecasts.io/covid/), but we could match it to only about a half of our sample. We, therefore, decided not to use this metric.
3. Given the panel structure of our data, it should be noted that both early and late mandate adoption variables are not mutually exclusive static measurements for country-day pairs, but they are dynamic variables that change over time within each country. According to our coding scheme, for instance, the day a mandate went into effect gets coded 1 (either for early or late adoption group) and it stays throughout until the last day data point, but the preceding days are coded 0. For those days, all three variables (early, late, and no-adoption) are coded 0.
4. The 19 subcontinents we classify and use are (1) North America, (2) the Caribbean and Central America, (3) South America, (4) East Asia, (5) Southeast Asia, (6) South Asia, (7) Central Asia, (8) West Asia, (9) Oceania, (10) Northern Europe, (11) Eastern Europe, (12) Southern Europe, (13) Western Europe, (14) Eastern Africa, (15) Southern Africa, (16) Northern Africa, (17) Central Africa, (18) Western Africa, and (19) the Middle East.
5. We thus do not include the percent of the older population aged 65 or more, but substituting the national median age with this variable does not change the results in any substantive way. Including population density additionally does not change the results, either.
6. The stringent assumption is that all unobservable individual country effects are uncorrelated with the independent variables in the model.
7. In this model, we do not use a log specification for the dependent variable. With the country fixed-effects in place and the main binary independent variables (six policy mandates) capturing a change at only one time in the longitudinal data structure, the log-binary specification effectively suppresses the variations of an outcome variable to the extent that the model cannot precisely estimate any associations, let alone predicting wrong directions for all policy mandates.
8. In addition, we further examined if the results hold when partial mandates' dynamic coding is decomposed into early, late, and non-adoption categories as well. Early partial mask mandates did not show any relationship but the result for early strict mask mandates substantively remained in place, suggesting the importance of both nationwide scale and early intervention timing for the long-term efficacy of mask mandates.
9. By definition, countries that never adopted the nation-wide mask mandates were not included in the distribution on the number of days taken to adopt the measure. Hence, they are coded as 0 for the adoption timing.
10. The world average and standard deviation estimates of infection rate were used from the cross-sectional analysis in Figure 4.

11. Alternatively, we used the Global Health Security (GHS) Index in place of hospital beds (sample size $n = 96$). Individualistic culture remains a significant predictor at the 0.05 level in the expected direction (odd ratio: 0.478, standard errors: 0.137, z-statistic: 2.57), but the GHS index was not significant, yielding an estimate in the opposite direction. (odd ratio: 0.980, standard errors: 0.023, z-statistic: 0.86). While the GHS is a comprehensive index, aggregating 85 sub-indicators across six categories (see https://www.ghsindex.org/), our analysis concurs with recent critiques that it skews the indicators toward the priorities of high-income countries (Razavi, Erondu, & Okereke, 2020), not predictive of government responses to coronavirus even among the OECD countries (Abbey et al., 2020), and its prediction on COVID-19 outcomes is in the opposite direction for a wide range of countries (Aitken et al., 2020).
12. We repeated the analysis in Figure 6, after excluding South Korea and Japan (i.e., $n = 87$). Individualistic culture still remains as a significant predictor at the 0.05 level (odd ratio: 0.448, Standard Errors: 0.175, z-statistic: 2.06), but hospital beds per population slightly loses its predictive power at the same level as expected (odd ratio: 1.498, standard errors: 0.315, z-statistic: 1.92).

References

Abaluck, Jason, Laura H Kwong, Ashley Styczynski, Ashraful Haque, Md. Alamgir Kabir, Ellen Bates-Jefferys, Emily Crawford, Jade Benjamin-Chung, Salim Benhachmi, Shabib Raihan, Shadman Rahman, Neeti Zaman, Peter J. Winch, Md. Maqsud Hossain, Hasan Mahmud Reza Stephen P. Luby, and Ahmed Mushfiq Mobarak. 2021. Normalizing Community Mask-Wearing: A Cluster Randomized Trial in Bangladesh. *National Bureau of Economic Research* (No. w28734). https://www.nber.org/papers/w28734.

Abbey, Enoch J., Banda A.A. Khalifa, Modupe O. Oduwole, Samuel K. Ayeh, Richard D. Nudotor, Emmanuella L. Salia, Oluwatobi Lasisi, Seth Bennett, Hasiya E. Yusuf, Allison L. Agwu, and Petros C. Karakousis. 2020. The Global Health Security Index Is Not Predictive of Coronavirus Pandemic Responses among Organization for Economic Cooperation and Development Countries. *PLoS One* 15(10): e0239398. https://doi.org/10.1371/journal.pone.0239398.

Aitken, Tess, Ken Lee Chin, Danny Liew, and Richard Ofori-Asenso. 2020. Rethinking Pandemic Preparation: Global Health Security Index (GHSI) Is Predictive of COVID-19 Burden, but in the Opposite Direction. *The Journal of Infection* 81(2): 318–56. https://doi.org/10.1016/j.jinf.2020.05.001.

Alagoz, Oguzhan, Ajay K. Sethi, Brian W. Patterson, Matthew Churpek, and Nasia Safdar. 2020. Effect of Timing of and Adherence to Social Distancing Measures on COVID-19 Burden in the United States: A Simulation Modeling Approach. *Annals of Internal Medicine* 174: 50–7. https://doi.org/10.7326/M20-4096.

Aldrich, Daniel P. 2020. The Need for Comparative Research in Disaster Studies: Developing Broader Theories from Research. In *Disaster Studies* 77–89. Singapore: Springer. https://doi.org/10.1007/978-981-32-9339-7_3.

Alesina, Alberto, and Paola Giuliano. 2015. Culture and Institutions. *Journal of Economic, Culture and Institutions Literature* 53(4): 898–944. https://doi.org/10.1257/jel.53.4.898.

Amuedo-Dorantes, Catalina, Neeraj Kaushal, and Ashley N. Muchow. 2020. Is the Cure Worse than the Disease? County-Level Evidence from the COVID-19 Pandemic in the United States. No. w27759. National Bureau of Economic Research. https://doi.org/10.3386/w27759.

An, Brian Y., and Shui-Yan Tang. 2020. Lessons from COVID-19 Responses in East Asia: Institutional Infrastructure and Enduring Policy Instruments. *The American Review of Public Administration* 50(6–7): 790–800. https://doi.org/10.1177/0275074020943707.

Anderson, Roy M., Hans Heesterbeek, Don Klinkenberg, and T. Déirdre Hollingsworth. 2020. How Will Country-Based Mitigation Measures Influence the Course of the COVID-19 Epidemic? *The Lancet* 395(10228): 931–4. https://doi.org/10.1016/S0140-6736(20)30567-5.

Ansell, Christopher K., Jarle Trondal, and Morten Øgård, eds. 2017. *Governance in Turbulent Times*. Oxford University Press.

Badr, Hamada S., Du Hongru, Maximilian Marshall, Ensheng Dong, Marietta M. Squire, and Lauren M. Gardner. 2020. Association between Mobility Patterns and COVID-19 Transmission in the USA: A Mathematical Modelling Study. *The Lancet Infectious Diseases* 20(11): 1247–54. https://doi.org/10.1016/S1473-3099(20)30553-3.

Baldwin, Peter. 2021. *Fighting the First Wave: Why the Coronavirus Was Tackled So Differently across the Globe*. New York: Cambridge University Press.

Bel, Germà, Óscar Gasulla, and Ferran A. Mazaira-Font. 2021. The Effect of Health and Economic Costs on governments' Policy Responses to COVID-19 Crisis under Incomplete Information. *Public Administration Review* 81(6): 1131–46. https://doi.org/10.1111/puar.13394.

Betsch, Cornelia, Lars Korn, Philipp Sprengholz, Lisa Felgendreff, Sarah Eitze, Philipp Schmid, and Robert Böhm. 2020. Social and Behavioral Consequences of Mask Policies during the COVID-19 Pandemic. *Proceedings of the National Academy of Sciences* 117(36): 21851–3. https://doi.org/10.1073/pnas.2011674117.

Boin, Arjen, Paul't Hart, Eric Stern, and Bengt Sundelius. 2016. *The Politics of Crisis Management: Public Leadership under Pressure*. Cambridge University Press.

Boin, Arjen, Allan McConnell, and Paul't Hart. 2021. *Governing the Pandemic: The Politics of Navigating a Mega-Crisis*. Springer Nature. https://doi.org/10.1007/978-3-030-72680-5.

Bouckaert, Geert, Davide Galli, Sabine Kuhlmann, Renate Reiter, and Steven Van Hecke. 2020. European Coronationalism? A Hot Spot Governing a Pandemic Crisis. *Public Administration Review* 80(5): 765–73. https://doi.org/10.1111/puar.13242.

Cacciapaglia, Giacomo, Corentin Cot, and Francesco Sannino. 2020. Second Wave COVID-19 Pandemics in Europe: A Temporal Playbook. *Scientific Reports* 10(1): 1–8. https://doi.org/10.1038/s41598-020-72611-5.

Cameron, A. Colin, and Douglas L. Miller. 2015. A practitioner's Guide to Cluster-Robust Inference. *Journal of Human Resources* 50(2): 317–72. https://doi.org/10.3368/jhr.50.2.317.

Capano, Giliberto, Michael Howlett, Darryl S.L. Jarvis, M. Ramesh, and Nihit Goyal. 2020. Mobilizing Policy (in) Capacity to Fight COVID-19: Understanding Variations in State Responses. *Policy and Society* 39(3): 285–308. https://doi.org/10.1080/14494035.2020.1787628.

Chen, Diqiang, Diefeng Peng, Marc Oliver Rieger, and Mei Wang. 2021. Institutional and Cultural Determinants of Speed of Government Responses during COVID-19 Pandemic. *Humanities and Social Sciences Communications* 8(1): 1–9. https://doi.org/10.1057/s41599-021-00844-4.

Cheng, Hao-Yuan, Shu-Wan Jian, Ding-Ping Liu, Ta-Chou Ng, Wan-Ting Huang, and Hsien-Ho Lin. 2020. Contact Tracing Assessment of COVID-19 Transmission Dynamics in Taiwan and Risk at Different Exposure Periods before and after Symptom Onset. *JAMA Internal Medicine* 180(9): 1156–63. https://doi.org/10.1001/jamainternmed.2020.2020.

Chernozhukov, Victor, Hiroyuki Kasahara, and Paul Schrimpf. 2021. Causal Impact of Masks, Policies, Behavior on Early Covid-19 Pandemic in the US. *Journal of Econometrics* 220(1): 23–62. https://doi.org/10.1016/j.jeconom.2020.09.003.

Child, Jenny, Eija Erasmus, Jacob Johnson and Rolland Dillon. 2020. Collaboration in Crisis: Reflecting on Australia's COVID-19 Response. McKinsey & Company, December 15, 2020, https://www.mckinsey.com/industries/public-and-social-sector/our-insights/collaboration-in-crisis-reflecting-on-australias-covid-19-response [accessed February 21, 2021].

Christensen, Tom, and Per Lægreid. 2020. Balancing Governance Capacity and Legitimacy: How the Norwegian Government Handled the COVID-19 Crisis as a High Performer. *Public Administration Review* 80(5): 774–9. https://doi.org/10.1111/puar.13241.

Churchman, West C. 1967. Wicked Problems. *Management Science* 14(4): 141–6. https://doi.org/10.1287/mnsc.14.4.B141.

Comfort, Louise K., Arjen Boin, and Chris C. Demchak, eds. 2010. *Designing Resilience: Preparing for Extreme Events*. University of Pittsburgh Press.

Comfort, Louise K., Naim Kapucu, Kilkon Ko, Scira Menoni, and Michael Siciliano. 2020. Crisis Decision-Making on a Global Scale: Transition from Cognition to Collective Action under Threat of COVID-19. *Public Administration Review* 80(4): 616–22. https://doi.org/10.1111/puar.13252.

Dahl, Robert Alan, and Charles Edward Lindblom. 1992. *Politics, Economics and Welfare*. New York: Routledge.

Dai, Bibing, Fu Di, Guangteng Meng, Bingsheng Liu, Qi Li, and Xun Liu. 2020. The Effects of Governmental and Individual Predictors on COVID-19 Protective Behaviors in China: A Path Analysis Model. *Public Administration Review* 80(5): 797–804. https://doi.org/10.1111/puar.13236.

Davies, Nicholas G., Petra Klepac, Liu Yang, Kiesha Prem, Mark Jit, and Rosalind M. Eggo. 2020. Age-Dependent Effects in the Transmission and Control of COVID-19 Epidemics. *Nature Medicine* 26(8): 1205–11. https://doi.org/10.1038/s41591-020-0962-9.

De Seve, G. Edward. 2020. Agile Government and Agile Governance: We Need Both. Agile Government Center, National Academy of Public Administration. https://napawash.org/grand-challenges-blog/agile-government-and-agile-governance-we-need-both.

Dehning, Jonas, Zierenberg Johannes, F. Paul Spitzner, Michael Wibral, Joao Pinheiro Neto, Michael Wilczek, and Viola Priesemann. 2020. Inferring Change Points in the Spread of COVID-19 Reveals the Effectiveness of Interventions. *Science* 369(6500): eabb9789. https://doi.org/10.1126/science.abb9789.

Dowd, Jennifer Beam, Liliana Andriano, David M. Brazel, Valentina Rotondi, Per Block, Xuejie Ding, Yan Liu, and Melinda C. Mills. 2020. Demographic Science Aids in Understanding the Spread and Fatality Rates of COVID-19. *Proceedings of the National Academy of Sciences* 117(18): 9696–8. https://doi.org/10.1073/pnas.2004911117.

Downey, Davia Cox, and William M. Myers. 2020. Federalism, Intergovernmental Relationships, and Emergency Response: A Comparison of Australia and the United States. *The American Review of Public Administration* 50(6–7): 526–35. https://doi.org/10.1177/0275074020941696.

Ferguson, Neil, Daniel Laydon, Gemma Nedjati Gilani, Natsuko Imai, Kylie Ainslie, Marc Baguelin, Sangeeta Bhatia, Adhiratha Boonyasiri, Zulma Cucunubá, Gina Cuomo-Dannenburg, Amy Dighe, Ilaria Dorigatti, Han Fu, Katy Gaythorpe, Will Green, Arran Hamlet, Wes Hinsley, Lucy C. Okell, Sabine van Elsland, Hayley Thompson, Robert Verity, Erik Volz, Haowei Wang, Yuanrong Wang, Patrick G.T. Walker, Caroline Walters, Peter Winskill, Charles Whittaker, Christl A. Donnelly, Steven Riley, and Azra C. Ghani. 2020. Report 9: Impact of Non-pharmaceutical Interventions (NPIs) to Reduce COVID19 Mortality and Healthcare Demand. *Imperial College London* 10(77482): 491–7. https://doi.org/10.25561/77482.

Flaxman, Seth, Swapnil Mishra, Gandy Axel, H. Juliette, T. Unwin, Thomas A. Mellan, Helen Coupland, Charles Whittaker, Harrison Zhu, Tresnia Berah, Jeffrey W. Eaton, Mélodie Monod, Imperial College COVID-19 Response Team, Azra C. Ghani, Christl A. Donnelly, Steven Riley, Michaela A.C. Vollmer, Neil M. Ferguson, Lucy C. Okell, and Samir Bhatt. 2020. Estimating the Effects of Non-pharmaceutical Interventions on COVID-19 in Europe. *Nature* 584(7820): 257–61. https://doi.org/10.1038/s41586-020-2405-7.

Fukuyama, Francis. 2020. The Pandemic and Political Order. *Foreign Affairs* 99: 26.

Gaynor, Tia Sherèe, and Meghan E. Wilson. 2020. Social Vulnerability and Equity: The Disproportionate Impact of COVID-19. *Public Administration Review* 80(5): 832–8. https://doi.org/10.1111/puar.13264.

Gelfand, Michele J., Jana L. Raver, Lisa Nishii, Lisa M. Leslie, Janetta Lun, Beng Chong Lim, Lili Duan, A. Almaliach, S. Ang, J. Arnadottir, Z. Aycan, K. Boehnke, P. Boski, R. Cabecinhas, D. Chan, J. Chhokar, A. D'Amato, M. Ferrer, I.C. Fischlmayr, R. Fischer, M. Fulop, J. Georgas, E.S. Kashima, Y. Kashima, K. Kim, A. Lempereur, P. Marquez, R. Othman, B. Overlaet, P. Panagiotopoulou, K. Peltzer, L.R. Perez-Florizno, L. Ponomarenko, A. Realo, V. Schei, M. Schmitt, P.B. Smith, N. Soomro, E. Szabo, N. Taveesin, M. Toyama, E. van de Vliert, N. Vohra, C. Ward, and S. Yamaguchi. 2011. Differences between Tight and Loose Cultures: A 33-Nation Study. *Science* 332(6033): 1100–4. https://doi.org/10.1126/science.1197754.

George, Bert, Bram Verschuere, Ellen Wayenberg, and Bishoy Louis Zaki. 2020. A Guide to Benchmarking COVID-19 Performance Data. *Public Administration Review* 80(4): 696–700. https://doi.org/10.1111/puar.13255.

Gourinchas, Pierre-Olivier, Şebnem Kalemli-Özcan, Veronika Penciakova, and Nick Sander. 2020. Covid-19 and SME Failures. No. w27877. National Bureau of Economic Research. https://doi.org/10.3386/w27877.

Gupta, Sumedha, Thuy D. Nguyen, Felipe Lozano Rojas, Shyam Raman, Byungkyu Lee, Ana Bento, Kosali I. Simon, and Coady Wing. 2020. Tracking public and private responses to the COVID-19 epidemic: evidence from state and local government actions No. w27027. National Bureau of Economic Research. https://doi.org/10.3386/w27027.

Haug, Nils, Lukas Geyrhofer, Alessandro Londei, Elma Dervic, Amélie Desvars-Larrive, Vittorio Loreto, Beate Pinior, Stefan Thurner, and Peter Klimek. 2020. Ranking the Effectiveness of Worldwide COVID-19 Government Interventions. *Nature Human Behaviour* 4(12): 1303–12. https://doi.org/10.1038/s41562-020-01009-0.

Haushofer, Johannes, and C. Jessica E. Metcalf. 2020. Which Interventions Work Best in a Pandemic? *Science* 368(6495): 1063–5. https://doi.org/10.1126/science.abb6144.

Hoang, Van Minh, Hong Hanh Hoang, Quynh Long Khuong, Ngoc Quang La, and Thi Tuyet Hanh Tran. 2020. Describing the Pattern of the COVID-19 Epidemic in Vietnam. *Global Health Action* 13(1): 1–6. https://doi.org/10.1080/16549716.2020.1776526.

Hofstede, Geert. 1980. *Culture's Consequences: International Differences in Work-Related Values*. Beverly Hills, CA: Sage Publications.

Holman, Naomi, Peter Knighton, Partha Kar, Jackie O'Keefe, Matt Curley, Andy Weaver, Emma Barron, Chirag Bakhai, Kamlesh Khunti, Nicholas J. Wareham, Naveed Sattar, Bob Young, and Jonathan Valabhji. 2020. Risk Factors for COVID-19-Related Mortality in People with Type 1 and Type 2 Diabetes in England: A Population-Based Cohort Study. *Lancet* 8(10): 823–33. https://doi.org/10.1016/S2213-8587(20)30271-0.

Hood, Christopher. 1986. *The Tools of Government*. Chatham, NJ: Chatham House.

Howlett, Michael. 2019. *Designing Public Policies: Principles and Instruments*. Routledge.

Howlett, Michael, and Achim Kemmerling. 2017. Calibrating Climate Change Policies: The Causes and Consequences of Sustained under-Reaction. *Journal of Environmental Policy & Planning* 19(6): 625–37. https://doi.org/10.1080/1523908X.2017.1324772.

IHME COVID-19 Forecasting Team. 2021. Modeling COVID-19 Scenarios for the United States. *Nature Medicine* 27(1): 94–105. https://doi.org/10.1038/s41591-020-1132-9.

Janssen, Marijn, and Haiko Van Der Voort. 2016. Adaptive Governance: Towards a Stable, Accountable and Responsive Government. *Government Information Quarterly* 33(1): 1–5. https://doi.org/10.1016/j.giq.2016.02.003.

Johansen, Morgen, ed. 2019. *Social Equity in the Asia-Pacific Region: Conceptualizations and Realities.* Palgrave Macmillan. https://doi.org/10.1007/978-3-030-15919-1.

Jones, Bryan D., Herschel F. Thomas, III, and Michelle Wolfe. 2014. Policy Bubbles. *Policy Studies Journal* 42(1): 146–71. https://doi.org/10.1111/psj.12046.

Kapucu, Naim. 2008. Collaborative Emergency Management: Better Community Organising, Better Public Preparedness and Response. *Disasters* 32(2): 239–62. https://doi.org/10.1111/j.1467-7717.2008.01037.x.

Kelman, Steven. 1981. *What Price Incentives? Economists and the Environment*. Boston, MA: Auburn House.

Khan, Jahidur Rahman, Nabil Awan, Md Islam, and Olav Muurlink. 2020. Healthcare Capacity, Health Expenditure, and Civil Society as Predictors of COVID-19 Case Fatalities: A Global Analysis. *Frontiers in Public Health* 8: 347. https://doi.org/10.3389/fpubh.2020.00347.

Knott, Jack H., and Gary J. Miller. 1987. *Reforming Bureaucracy: The Politics of Institutional Choice*. Englewood Cliffs, NJ: Prentice Hall.

Kraemer, Moritz U.G., Chia-Hung Yang, Bernardo Gutierrez, Chieh-Hsi Wu, Brennan Klein, David M. Pigott, Louis Du Plessis, Nuno R. Faria, Ruoran Li, William P. Hanage, John S. Brownstein, Maylis Layan, Alessandro Vespignani, Huaiyu Tian, Christopher Dye, Liver G. Pybus, and Samuel V. Scarpino. 2020. The Effect of Human Mobility and Control Measures on the COVID-19 Epidemic in China. *Science* 368(6490): 493–7. https://doi.org/10.1126/science.abb4218.

Lai, Shengjie, Nick W. Ruktanonchai, Liangcai Zhou, Olivia Prosper, Wei Luo, Jessica R. Floyd, Amy Wesolowski, Mauricio Santillana, Chi Zhang, Xiangjun du, Hongjie Yu, and Andrew J. Tatem. 2020. Effect of Non-pharmaceutical Interventions to Contain COVID-19 in China. *Nature* 585(7825): 410–3. https://doi.org/10.1038/s41586-020-2293-x.

Lauer, Stephen A., Kyra H. Grantz, Qifang Bi, Forrest K. Jones, Qulu Zheng, Hannah R. Meredith, Andrew S. Azman, Nicholas G. Reich, and Justin Lessler. 2020. The Incubation Period of Coronavirus Disease 2019 (COVID-19) from Publicly Reported Confirmed Cases: Estimation and Application. *Annals of Internal Medicine* 172(9): 577–82. https://doi.org/10.7326/M20-0504.

Lee, Seungjae, Tark Kim, Eunjung Lee, Cheolgu Lee, Hojung Kim, Heejeong Rhee, Se Yoon Park, Hyo-Ju Son, Shinae Yu, Jung Wan Park, Eun Ju Choo, Suyeon Park, Mark Loeb, and Tae Hyong Kim. 2020. Clinical Course and Molecular Viral Shedding among Asymptomatic and Symptomatic Patients with SARS-CoV-2 Infection in a Community Treatment Center in the Republic of Korea. *JAMA Internal Medicine* 180(11): 1447–52. https://doi.org/10.1001/jamainternmed.2020.3862.

Leung, Nancy H.L., Daniel K.W. Chu, Eunice Y.C. Shiu, Kwok-Hung Chan, James J. McDevitt, Benien J.P. Hau, Hui-Ling Yen, Yuguo Li, Dennis K.M. Ip, J.S. Malik Peiris, Wing-Hong Seto, Gabriel M. Leung, Donald K. Milton, and Benjamin J. Cowling. 2020. Respiratory Virus Shedding in Exhaled Breath and Efficacy of Face Masks. *Nature Medicine* 26(5): 676–80. https://doi.org/10.1038/s41591-020-0843-2.

Li, Ruiyun, Sen Pei, Bin Chen, Yimeng Song, Tao Zhang, Yang Wan, and Jeffrey Shaman. 2020. Substantial Undocumented Infection Facilitates the Rapid Dissemination of Novel Coronavirus (SARS-CoV-2). *Science* 368(6490): 489–93. https://doi.org/10.1126/science.abb3221.

Liang, Li-Lin, Ching-Hung Tseng, Hsiu J. Ho, and Wu. Chun-Ying. 2020. COVID-19 Mortality Is Negatively Associated with Test Number and Government Effectiveness. *Scientific Reports* 10(1): 1–7. https://doi.org/10.1038/s41598-020-68862-x.

Lindberg, Staffan I., Michael Coppedge, John Gerring, and Jan Teorell. 2014. V-DEM: A New Way to Measure Democracy. *Journal of Democracy* 25(3): 159–69. https://doi.org/10.1353/jod.2014.0040.

Linder, Stephen H., and B. Guy Peters. 1989. Instruments of Government: Perceptions and Contexts. *Journal of Public Policy* 9(1): 35–58. https://doi.org/10.1017/S0143814X00007960.

Lu, Jackson G., Peter Jin, and Alexander S. English. 2021. Collectivism Predicts Mask Use during COVID-19. *Proceedings of the National Academy of Sciences of the United States of America* 118(23): 1–8. https://doi.org/10.1073/pnas.2021793118.

Lyu, Wei, and George L. Wehby. 2020. Community Use of Face Mask and COVID-19: Evidence from a Natural Experiment of State Mandates in the US. *Health Affairs* 39(8): 1419–25. https://doi.org/10.1377/hlthaff.2020.00818.

Maor, Moshe. 2012. Policy Overreaction. *Journal of Public Policy* 32(3): 231–59. https://doi.org/10.1017/S0143814X1200013X.

———. 2014. Policy Bubbles: Policy Overreaction and Positive Feedback. *Governance* 27(3): 469–87. https://doi.org/10.1111/gove.12048.

Martin-Howard, Simone, and Kyle Farmbry. 2020. Framing a Needed Discourse on Health Disparities and Social Inequities: Drawing Lessons from a Pandemic. *Public Administration Review* 80(5): 839–44. https://doi.org/10.1111/puar.13265.

McCann, Joseph, John Selsky, and James Lee. 2009. Building Agility, Resilience and Performance in Turbulent Environments. *People & Strategy* 32(3): 44–51 http://agilityconsulting.com/resources/Strategic%20Agility%20Institute/HRPS-BuildingAgility.pdf [accessed February 21, 2021].

McKibbin, Warwick, and Roshen Fernando. 2020. The Global Macroeconomic Impacts of COVID-19: Seven Scenarios. *Asian Economic Papers*: 1–55. https://doi.org/10.1162/asep_a_00796.

Mehari, Yeabsira. 2020. The Role of Social Trust in Citizen Mobility During COVID-19. Working Paper. https://ssrn.com/abstract=3607668 [accessed February 21, 2021].

Menifield, Charles E., and Cal Clark. 2021. Pandemic Planning in the United States: An Examination of COVID-19 Data. *Public Administration Review* 81(6): 1102–9. https://doi.org/10.1111/puar.13326.

Mergel, Ines, Sukumar Ganapati, and Andrew B. Whitford. 2020. Agile: A New Way of Governing. *Public Administration Review* 81: 161–5. https://doi.org/10.1111/puar.13202.

Mistur, Evan, John Wagner Givens, and Daniel Matisoff. 2020. Contagious COVID-19 Policies: Policy Diffusion During Times of Crisis. Working paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3662444 [accessed February 21, 2021].

Moe, Terry M. 1995. Toward a theory of public bureaucracy. In *Organization Theory: From Chester Barnard to the Present and Beyond*, edited by Oliver E. Williamson, 116–53.

Moloney, Kim, and Susan Moloney. 2020. Australian Quarantine Policy: From Centralization to Coordination with Mid-Pandemic COVID-19 Shifts. *Public Administration Review* 80(4): 671–82. https://doi.org/10.1111/puar.13224.

Moon, M. Jae. 2020. Fighting against COVID-19 with Agility, Transparency, and Participation: Wicked Policy Problems and New Governance Challenges. *Public Administration Review* 80(4): 651–6. https://doi.org/10.1111/puar.13214.

Pedersen, Mogens Jin, and Nathan Favero. 2020. Social Distancing during the COVID-19 Pandemic: Who Are the Present and Future Noncompliers? *Public Administration Review* 80(5): 805–14. https://doi.org/10.1111/puar.13240.

Peeples, Lynne. 2020. What the Data Say about Wearing Face Masks. *Nature* 586: 186–9. https://doi.org/10.1038/d41586-020-02801-8.

Pei, Sen, Sasikiran Kandula, and Jeffrey Shaman. 2020. Differential Effects of Intervention Timing on COVID-19 Spread in the United States. *Science Advances* 6(49): eabd6370. https://doi.org/10.1126/sciadv.abd6370.

Perry, Ronald W., Michael K. Lindell, and Kathleen J. Tierney, eds. 2001. *Facing the Unexpected: Disaster Preparedness and Response in the United States*. Joseph Henry Press.

Persson, Thomas, Charles F. Parker, and Sten Widmalm. 2017. Social Trust, Impartial Administration and Public Conference in EU Crisis Management Institutions. *Public Administration* 95(1): 97–114. https://doi.org/10.1111/padm.12295.

Porcher, Simon. 2020. Response2covid19, a Dataset of Governments' Responses to COVID-19 All around the World. *Scientific Data* 7(1): 1–9. https://doi.org/10.1038/s41597-020-00757-y.

———. 2021. Culture and the Quality of Government. *Public Administration Review* 81(2): 333–43. https://doi.org/10.1111/puar.13106.

Porcher, Simon, and Thomas Renault. 2021. Social Distancing Beliefs and Human Mobility: Evidence from Twitter. *PLoS One* 16: e0246949. https://doi.org/10.1371/journal.pone.0246949.

Puppim de Oliveira, Jose A., and Evan Berman. 2021. Exposing the Unfinished Business of Building Public Administration in Late Democracies: Lessons from the COVID-19 Response in Brazil. *Public Administration Review* 81(6): 1183–91. https://doi.org/10.1111/puar.13415.

Rahmandad, Hazhir, Tse Yang Lim, and John Sterman. 2020. Estimating COVID-19 Under-Reporting across 86 Nations: Implications for Projections and Control. *medRxiv*. https://doi.org/10.1101/2020.06.24.20139451.

Ramírez de la Cruz, Edgar E., Eduardo José Grin, Pablo Sanabria-Pulido, Daniel Cravacuore, and Arturo Orellana. 2020. The Transaction Costs of Government Responses to the COVID-19 Emergency in Latin America. *Public Administration Review* 80(4): 683–95. https://doi.org/10.1111/puar.13259.

Razavi, Ahmed, Ngozi A. Erondu, and Ebere Okereke. 2020. The Global Health Security Index: What Value Does it Add? *BMJ Global Health* 5(4): e002477. https://doi.org/10.1136/bmjgh-2020-002477.

Rittel, Horst W.J., and Melvin M. Webber. 1973. Dilemmas in a General Theory of Planning. *Policy Sciences* 4(2): 155–69. https://doi.org/10.1007/BF01405730.

Room, Graham. 2011. *Complexity, Institutions and Public Policy: Agile Decision-Making in a Turbulent World*. Edward Elgar Publishing.

Salamon, Lester M. 1981. Rethinking Public Management: Third-Party Government and the Changing Forms of Government Action. *Public Policy* 29(3): 255–75.

Savvides, Christina, and Robert Siegel. 2020. Asymptomatic and Pre-Symptomatic Transmission of SARS-CoV-2: A Systematic Review. *medRxiv*. https://doi.org/10.1101%2F2020.06.11.20129072.

Schlosser, Frank, Benjamin F. Maier, Olivia Jack, David Hinrichs, Adrian Zachariae, and Dirk Brockmann. 2020. COVID-19 Lockdown Induces Disease-Mitigating Structural Changes in Mobility Networks. *Proceedings of the National Academy of Sciences* 117(52): 32883–90. https://doi.org/10.1073/pnas.2012326117.

Schuster, Christian, Lauren Weitzman, Kim Sass Mikkelsen, Jan Meyer-Sahling, Katherine Bersch, Francis Fukuyama, Patricia Paskov, Daniel Rogger, Dinsha Mistree, and Kerenssa Kay. 2020. Responding to COVID-19 through Surveys of Public Servants. *Public Administration Review* 80(5): 792–6. https://doi.org/10.1111/puar.13246.

Sebhatu, Abiel, Karl Wennberg, Stefan Arora-Jonsson, and Staffan I. Lindberg. 2020. Explaining the Homogeneous Diffusion of COVID-19 Nonpharmaceutical Interventions across Heterogeneous Countries. *Proceedings of the National Academy of Sciences* 117(35): 21201–8. https://doi.org/10.1073/pnas.2010625117.

Spelta, Alessandro, Andrea Flori, Francesco Pierri, Giovanni Bonaccorsi, and Fabio Pammolli. 2020. After the Lockdown: Simulating Mobility, Public Health and Economic Recovery Scenarios. *Scientific Reports* 10(1): 1–13. https://doi.org/10.1038/s41598-020-73949-6.

Stivers, Camilla. 2021. Public Service in the Pandemic Era: A COVID Commentary. *Public Administration Review*. https://doi.org/10.1111/puar.13350.

Tartof, Sara Y., Lei Qian, Vennis Hong, Rong Wei, Ron F. Nadjafi, Heidi Fischer, Zhuoxin Li, Sally F. Shaw, Susan L. Caparosa, Claudia L. Nau, Tanmai Saxena, Gunter K. Rieg, Bradley K. Ackerson, Adam L. Sharp, Jacek Skarbinski, Tej K. Naik, and Sameer B. Murali. 2020. Obesity and Mortality among Patients Diagnosed with COVID-19: Results from an Integrated Health Care Organization. *Annals of Internal Medicine* 173(10): 773–81. https://doi.org/10.7326/M20-3742.

Tian, Ting, Wenxiang Luo, Jianbin Tan, Yukang Jiang, Minqiong Chen, Wenliang Pan, Songpan Yang, Jiashu Zhao, Xueqin Wang, and Heping Zhang. 2021. The Timing and Effectiveness of Implementing Mild Interventions of COVID-19 in Large Industrial Regions Via a Synthetic Control Method. *Statistics and Its Interface* 14(1): 3–12. https://doi.org/10.4310/20-SII634.

Turrini, Alex, Daniela Cristofoli, and Giovanni Valotti. 2020. Sense or Sensibility? Different Approaches to Cope with the COVID-19 Pandemic. *American Review of Public Administration* 50(6–7): 746–52. https://doi.org/10.1177/0275074020942427.

Van Dooren, Wouter, and Mirko Noordegraaf. 2020. Staging Science: Authoritativeness and Fragility of Models and Measurement in the COVID-19 Crisis. *Public Administration Review* 80(4): 610–5. https://doi.org/10.1111/puar.13219.

Van Tan, Le. 2021. COVID-19 Control in Vietnam. *Nature Immunology* 22(261): 261. https://doi.org/10.1038/s41590-021-00882-9.

Van Wart, Montgomery, and Naim Kapucu. 2011. Crisis Management Competencies. *Public Management Review* 13(4): 489–511. https://doi.org/10.1080/14719037.2010.525034.

Viner, Russell M., Simon J. Russell, Helen Croker, Jessica Packer, Joseph Ward, Claire Stansfield, Oliver Mytton, Chris Bonell, and Robert Booy. 2020. School Closure and Management Practices during Coronavirus Outbreaks Including COVID-19: A Rapid Narrative Systematic Review. *Lancet* 4(5): 397–404. https://doi.org/10.1016/S2352-4642(20)30095-X.

van der Wal, Zeger, Caspar van den Berg, and M. Shamsul Haque. 2021. Comparative Public Administration in a Globalized World: Moving beyond Standard Assumptions toward Increased Understanding. *Public Administration Review* 81(2): 295–8. https://doi.org/10.1111/puar.13373.

Walker, Warren E., S. Adnan Rahman, and Jonathan Cave. 2011. Adaptive Policies, Policy Analysis, and Policy-Making. *European Journal of Operational Research* 128(2): 282–9. https://doi.org/10.1016/S0377-2217(00)00071-0.

Weng, Shi-Hong, Anna Ya Ni, Alfred Tat-Kei Ho, and Ruo-Xi Zhong. 2020. Responding to the Coronavirus Pandemic: A Tale of Two Cities. *The American Review of Public Administration* 50(6–7): 497–504. https://doi.org/10.1177/0275074020941687.

White, Easton R., and Laurent Hébert-Dufresne. 2020. State-Level Variation of Initial COVID-19 Dynamics in the United States. *PLoS One* 15(10): e0240648. https://doi.org/10.1371/journal.pone.0240648.

Xu, Jie, Sabiha Hussain, Guanzhu Lu, Kai Zheng, Shi Wei, Wei Bao, and Lanjing Zhang. 2020. Associations of Stay-at-Home Order and Face-Masking Recommendation with Trends in Daily New Cases and Deaths of Laboratory-Confirmed COVID-19 in the United States. *Exploratory Research and Hypothesis in Medicine*: 1–10. https://doi.org/10.14218/ERHM.2020.00045.

Yan, Bo, Xiaomin Zhang, Long Wu, Heng Zhu, and Bin Chen. 2020. Why Do Countries Respond Differently to COVID-19? A Comparative Study of Sweden, China, France, and Japan. *The American Review of Public Administration* 50(6–7): 762–9. https://doi.org/10.1177/0275074020942445.

Yancy, Clyde W. 2020. COVID-19 and African Americans. *JAMA* 323(19): 1891–2. https://doi.org/10.1001/jama.2020.6548.

Zheng, Shiming, Li Hongxia, and Sun Hao. 2021. Crisis lifecycle, policy response, and policy effectiveness. *Public Management Review* 1–27. http://dx.doi.org/10.1080/14719037.2021.1972683.

Appendix A

Table A1 Mandates' Short-Term Effects on New Case Rates

	(1)	(2)	(3)	(4)	(5)
			Rate of New Cases$_t$		
Lags for Mandates	5 Days	9 Days	12 Days	21 Days	30 Days
Mask mandates	−1.187***	−1.127***	−1.035***	−0.694**	−0.330*
	(0.227)	(0.227)	(0.222)	(0.211)	(0.153)
International travel bans	−0.386	−0.506*	−0.504*	−0.374*	−0.101
	(0.241)	(0.222)	(0.213)	(0.148)	(0.0934)
Domestic lockdowns	−0.0934	−0.0857	−0.103	−0.0749	−0.641***
	(0.155)	(0.163)	(0.154)	(0.122)	(0.136)
Mass gathering bans	−0.542*	−0.650*	−0.774**	−0.923***	−0.275*
	(0.197)	(0.236)	(0.245)	(0.212)	(0.108)
School closures	0.100	−0.312+	−0.486**	−0.716***	−0.0106
	(0.214)	(0.173)	(0.160)	(0.147)	(0.0973)
Restaurant closures	−0.149	−0.126	−0.122	−0.126	−0.821***
	(0.126)	(0.114)	(0.109)	(0.104)	(0.0969)
Rate of new cases$_{t-1}$	0.713***	0.707***	0.703***	0.706***	0.731***
	(0.00799)	(0.00754)	(0.00730)	(0.00798)	(0.00890)
Total cases per million$_{t-1}$	−6.51e−05	−6.82e−05	−7.07e−05	−7.30e−05	−6.77e−05
	(5.13e−05)	(5.21e−05)	(5.15e−05)	(4.82e−05)	(4.18e−05)
Total deaths per million$_{t-1}$	−0.00342**	−0.00340**	−0.00330**	−0.00282*	−0.00246*
	(0.00101)	(0.00111)	(0.00113)	(0.00109)	(0.000904)
Log (days since January 1)	−1.099**	−0.890*	−0.770*	−0.503	−0.395
	(0.298)	(0.338)	(0.352)	(0.366)	(0.332)
Constant	7.995***	7.416***	7.002***	5.620**	4.527**
	(1.398)	(1.569)	(1.625)	(1.630)	(1.541)
Observations	21,155	21,153	21,150	21,126	21,036
Within R^2	0.863	0.864	0.865	0.867	0.867
Between R^2	0.802	0.782	0.776	0.815	0.896
Number of countries	164	164	164	164	164
Country fixed-effects	Yes	Yes	Yes	Yes	Yes

Notes: Units of analysis are country-day pairs. Fixed-effects model with robust standard errors clustered by subcontinents in parentheses.
***$p < .001$.
**$p < .01$.
*$p < .05$.
+$p < .10$.

Table A2 Robustness Checks for A1 Using Dummies for Partial or Strict Order

	(1)	(2)	(3)	(4)	(5)
			Rate of New Cases$_t$		
Lags for Mandates	5 Days	9 Days	12 Days	21 Days	30 Days
Strict mask mandates	−1.137***	−1.098***	−1.015***	−0.697**	−0.341*
	(0.224)	(0.226)	(0.221)	(0.208)	(0.152)
Partial mask mandates	−0.865**	−0.879***	−0.845***	−0.637***	−0.286*
	(0.236)	(0.203)	(0.195)	(0.151)	(0.112)
Strict international travel bans	−0.372	−0.522*	−0.526*	−0.407*	−0.288*
	(0.255)	(0.245)	(0.239)	(0.167)	(0.115)
Partial international travel bans	−0.0344	−0.259	−0.301	−0.342+	−0.241+
	(0.228)	(0.246)	(0.248)	(0.180)	(0.131)
Strict domestic lockdowns	−0.0738	−0.0862	−0.118	−0.112	−0.144
	(0.167)	(0.167)	(0.155)	(0.114)	(0.0878)
Partial domestic lockdowns	−0.0133	0.0185	0.0281	0.0317	−0.0220
	(0.127)	(0.149)	(0.158)	(0.161)	(0.138)
Strict mass gathering bans	−0.567*	−0.646*	−0.766**	−0.902***	−0.613***
	(0.210)	(0.241)	(0.248)	(0.210)	(0.135)
Partial mass gathering bans	−0.181	−0.392	−0.560+	−0.765*	−0.500*
	(0.292)	(0.297)	(0.308)	(0.295)	(0.224)
Strict school closures	0.107	−0.327	−0.509*	−0.764***	−0.914***
	(0.241)	(0.198)	(0.189)	(0.172)	(0.116)
Partial school closures	0.218	−0.114	−0.268	−0.620**	−0.920***
	(0.252)	(0.225)	(0.237)	(0.173)	(0.139)
Strict restaurant closures	−0.174	−0.151	−0.142	−0.137	−0.00718
	(0.125)	(0.115)	(0.111)	(0.106)	(0.1000)
Partial restaurant closures	0.0398	0.0669	0.0616	0.0672	0.122
	(0.178)	(0.166)	(0.143)	(0.101)	(0.0993)
Rate of new cases$_{t-1}$	0.713***	0.707***	0.703***	0.706***	0.730***
	(0.00805)	(0.00757)	(0.00728)	(0.00793)	(0.00877)
Total cases per million$_{t-1}$	−6.86e−05	−7.19e−05	−7.45e−05	−7.75e−05	−7.23e−05+
	(4.90e−05)	(4.97e−05)	(4.91e−05)	(4.55e−05)	(3.98e−05)
Total deaths per million$_{t-1}$	−0.00320**	−0.00321**	−0.00313*	−0.00270*	−0.00240**
	(0.00102)	(0.00108)	(0.00109)	(0.000996)	(0.000808)
Log (days since January 1)	−1.164**	−0.852*	−0.682+	−0.297	−0.171
	(0.312)	(0.338)	(0.346)	(0.367)	(0.338)
Constant	8.242***	7.265***	6.650***	4.771**	3.584*
	(1.464)	(1.567)	(1.587)	(1.615)	(1.553)
Observations	21,155	21,153	21,150	21,126	21,036
Within R^2	0.863	0.864	0.865	0.867	0.867
Between R^2	0.799	0.786	0.784	0.826	0.902
Number of countries	164	164	164	164	164
Country fixed-effects	Yes	Yes	Yes	Yes	Yes

Notes: Units of analysis are country-day pairs. Fixed-effects model with robust standard errors clustered by subcontinents in parentheses.
****p* < .001.
***p* < .01.
**p* < .05.
+*p* < .10.

Table A3 Robustness Checks for A1 Using Mortality Rate as an Alternative Outcome

	(1)	(2)	(3)	(4)	(5)
	Rate of New Deaths$_t$				
Lags for Mandates	5 Days	9 Days	12 Days	21 Days	30 Days
Total cases per million$_{t-1}$	0.000195*	0.000180*	0.000167*	0.000130$^+$	0.000126
	(6.84e–05)	(6.94e-05)	(6.99e-05)	(6.88e-05)	(7.37e-05)
Total deaths per million$_{t-1}$	−0.0211***	−0.0206***	−0.0201***	−0.0189***	−0.0193***
	(0.00382)	(0.00392)	(0.00403)	(0.00439)	(0.00435)
Rate of new deaths$_{t-1}$	0.0556**	0.0504**	0.0473**	0.0397*	0.0464**
	(0.0160)	(0.0154)	(0.0151)	(0.0147)	(0.0155)
Log (days since 1 Jan 2020)	−8.976***	−9.021***	−9.096***	−7.461***	−6.381***
	(1.242)	(1.277)	(1.303)	(1.444)	(1.396)
Mask mandates	−1.816*	−1.782*	−1.659*	−0.871	−0.146
	(0.719)	(0.739)	(0.685)	(0.566)	(0.487)
International travel bans	−1.783***	−1.540**	−1.200*	−1.067**	−1.076**
	(0.454)	(0.421)	(0.433)	(0.322)	(0.327)
Domestic lockdowns	−0.0836	−0.372	−0.898*	−1.317***	−0.511
	(0.388)	(0.332)	(0.324)	(0.298)	(0.454)
Mass gathering bans	0.339	0.0703	0.000889	−1.228**	−0.490$^+$
	(0.572)	(0.455)	(0.443)	(0.420)	(0.256)
Schools closures	0.741	0.292	0.0440	−1.279*	−0.455
	(0.699)	(0.515)	(0.509)	(0.473)	(0.383)
Restaurants closures	−1.086*	−1.532**	−1.739**	−0.869*	−2.388***
	(0.428)	(0.394)	(0.448)	(0.375)	(0.391)
Constant	50.34***	51.22***	51.78***	44.87***	38.84***
	(6.330)	(6.256)	(6.344)	(6.910)	(6.615)
Observations	16,886	16,886	16,885	16,876	16,867
Within R^2	0.191	0.195	0.199	0.210	0.203
Between R^2	0.026	0.026	0.027	0.031	0.026
Number of countries	152	152	152	152	152
Country FE	Yes	Yes	Yes	Yes	Yes

Notes: Units of analysis are country-day pairs. Fixed-effects model with robust standard errors clustered by subcontinents in parentheses.
***$p<.001$.
**$p<.01$.
*$p<.05$.
$^+p<.10$.

Table A4 Robustness Checks for A3 Using Dummies for Partial or Strict Orders

	(1)	(2)	(3)	(4)	(5)
	Rate of New Deaths$_t$				
Lags for Mandates	5 Days	9 Days	12 Days	21 Days	30 Days
Total cases per million$_{t-1}$	0.000197*	0.000176*	0.000154+	0.000107	0.000110
	(8.56e–05)	(8.30e–05)	(8.41e–05)	(7.82e–05)	(7.97e–05)
Total deaths per million$_{t-1}$	−0.0209***	−0.0204***	−0.0200***	−0.0191***	−0.0199***
	(0.00428)	(0.00435)	(0.00443)	(0.00439)	(0.00402)
Rate of new deaths$_{t-1}$	0.0544**	0.0499**	0.0469**	0.0388*	0.0435*
	(0.0162)	(0.0154)	(0.0152)	(0.0149)	(0.0157)
Log (days since 1 Jan 2020)	−9.547***	−9.511***	−9.477***	−7.128***	−5.602**
	(1.242)	(1.341)	(1.399)	(1.509)	(1.461)
Strict mask mandates	−1.835*	−1.754*	−1.607*	−0.953	−0.368
	(0.745)	(0.753)	(0.700)	(0.580)	(0.467)
Partial mask mandates	−0.500	−0.511	−0.352	−0.0739	0.613
	(0.991)	(0.921)	(0.863)	(0.667)	(0.569)
Strict international travel bans	−1.720***	−1.428**	−1.054*	−1.137**	−0.624*
	(0.415)	(0.420)	(0.488)	(0.382)	(0.266)
Partial international travel bans	−0.104	0.0750	0.404	−0.657	−1.038**
	(0.419)	(0.417)	(0.473)	(0.478)	(0.339)
Strict domestic lockdowns	0.0833	−0.237	−0.819*	−1.296***	−1.108**
	(0.368)	(0.342)	(0.331)	(0.267)	(0.314)
Partial domestic lockdowns	−0.0504	−0.334	−0.678	−0.884+	−0.691
	(0.361)	(0.384)	(0.422)	(0.470)	(0.471)
Strict mass gathering bans	0.0617	−0.178	−0.214	−1.299**	−0.516
	(0.549)	(0.477)	(0.417)	(0.414)	(0.403)
Partial mass gathering bans	0.850	0.368	−0.00308	−1.634*	−1.469+
	(0.743)	(0.860)	(0.845)	(0.757)	(0.819)
Strict school closures	1.039	0.495	0.0950	−1.338*	−2.539***
	(0.736)	(0.516)	(0.499)	(0.527)	(0.401)
Partial school closures	1.042+	0.650	−0.0268	−1.448**	−2.911***
	(0.565)	(0.388)	(0.364)	(0.488)	(0.486)
Strict restaurant closures	−1.070*	−1.497**	−1.678**	−0.843*	−0.405
	(0.480)	(0.445)	(0.491)	(0.400)	(0.403)
Partial restaurant closures	0.362	−0.116	−0.246	0.208	0.427
	(0.566)	(0.562)	(0.592)	(0.472)	(0.359)
Constant	52.38***	53.02***	53.23***	43.55***	35.63***
	(6.226)	(6.445)	(6.683)	(7.109)	(6.852)
Observations	16,886	16,886	16,885	16,876	16,867
Within R^2	0.193	0.196	0.201	0.211	0.207
Between R^2	0.016	0.018	0.026	0.053	0.064
Number of countries	152	152	152	152	152
Country FE	Yes	Yes	Yes	Yes	Yes

Notes: Units of analysis are country-day pairs. Fixed-effects model with robust standard errors clustered by subcontinents in parentheses.
***$p < .001$.
**$p < .01$.
*$p < .05$.
+$p < .10$.

Table A5 Cross-Sectional Country-Level Analysis Full Results for Long-Term Impact

	(1)	(2)	(3)	(4)
	ln (averaged total cumulative infections per million between 90th and 120th day after the first case)			
Mask mandates within 14 days	−1.317***	−1.044***	−0.916*	−0.828*
	(0.314)	(0.197)	(0.337)	(0.294)
International travel bans within 14 days	−0.568	−0.139	−0.032	0.014
	(0.487)	(0.424)	(0.424)	(0.467)
Domestic lockdowns within 14 days	−0.380	0.146	−0.137	−0.256
	(0.238)	(0.290)	(0.319)	(0.325)
Mass gathering bans within 14 days	−0.122	−0.286	0.122	0.175
	(0.397)	(0.539)	(0.561)	(0.486)
School closures within 14 days	0.557	−0.016	0.080	0.009
	(0.472)	(0.423)	(0.493)	(0.450)
Restaurant closures within 14 days	−0.778	−0.604	−0.550	−0.479
	(0.421)	(0.482)	(0.471)	(0.503)
Mask mandates ever	0.497	0.311	0.302	0.193
	(0.290)	(0.319)	(0.276)	(0.286)
International travel bans ever	1.071+	0.374	0.097	0.121
	(0.592)	(0.380)	(0.320)	(0.318)
Domestic lockdowns ever	0.591+	−0.001	0.321	0.531
	(0.297)	(0.278)	(0.328)	(0.309)
Mass gathering bans ever	0.181	−0.118	−0.428	−0.101
	(0.410)	(0.514)	(0.507)	(0.487)
School closures ever	−0.880	−0.123	−0.353	−0.342
	(0.884)	(0.485)	(0.677)	(1.033)
Restaurant closures ever	1.019**	0.989+	0.758	0.438
	(0.303)	(0.493)	(0.447)	(0.440)
Hospital beds per 1,000 people		0.046	0.064	0.088
		(0.075)	(0.073)	(0.078)
Population with diabetes (%)		0.015	−0.013	−0.044
		(0.047)	(0.043)	(0.046)
Population with overweight (%)		0.066**	0.051**	0.050**
		(0.018)	(0.016)	(0.016)
Health expenditure in GDP (%)		−0.066	−0.059	−0.055
		(0.047)	(0.043)	(0.050)
National median age		−0.015	−0.035	−0.040
		(0.032)	(0.039)	(0.042)
GDP per capita (in thousand $)			0.034**	0.028*
			(0.009)	(0.011)
Government effectiveness			−0.001	−0.031
			(0.304)	(0.372)
Mortality rate from prior pandemic				0.0005
				(0.0005)
COVID-19 tests per million				0.00001*
				(0.000003)
Constant	3.774**	2.992*	4.094*	4.107*
	(1.159)	(1.117)	(1.569)	(1.791)
Observations	159	138	137	129
R^2	0.444	0.568	0.630	0.645
Five continent fixed-effects	Yes	Yes	Yes	Yes

Notes: Unit of analysis is country. Robust standard errors clustered by subcontinents in parenthesis.
***$p<.001$.
**$p<.01$.
*$p<.05$.
+$p<.10$.

Table A6 Robustness Checks for A5 Using Mortality Rate as an Alternative Outcome

	(1)	(2)	(3)	(4)
	ln (averaged total cumulative ***deaths*** per million between 90th and 120th day after the first case)			
Mask mandates within 14 days	−1.316**	−1.170**	−1.139*	−1.143*
	(0.428)	(0.320)	(0.512)	(0.498)
International travel bans within 14 days	−0.475	−0.086	−0.039	0.065
	(0.305)	(0.285)	(0.284)	(0.281)
Domestic lockdowns within 14 days	−0.597**	−0.170	−0.274	−0.275
	(0.166)	(0.239)	(0.269)	(0.236)
Mass gathering bans within 14 days	−0.196	−0.252	−0.076	0.037
	(0.273)	(0.371)	(0.379)	(0.347)
School closures within 14 days	0.123	−0.374	−0.373	−0.479
	(0.308)	(0.323)	(0.314)	(0.307)
Restaurant closures within 14 days	−0.400	−0.425	−0.419	−0.483
	(0.311)	(0.410)	(0.397)	(0.368)
Mask mandates ever	0.158	0.278	0.255	0.197
	(0.161)	(0.223)	(0.218)	(0.218)
International travel bans ever	0.703	0.200	0.078	0.061
	(0.444)	(0.252)	(0.245)	(0.247)
Domestic lockdowns ever	0.498*	0.322	0.431	0.494*
	(0.210)	(0.228)	(0.253)	(0.232)
Mass gathering bans ever	0.393	0.153	0.034	0.210
	(0.351)	(0.429)	(0.426)	(0.379)
School closures ever	0.229	0.612	0.607	0.730
	(0.436)	(0.386)	(0.471)	(0.637)
Restaurant closures ever	0.643*	0.519	0.444	0.244
	(0.302)	(0.374)	(0.371)	(0.369)
Hospital beds per 1,000 people		−0.009	−0.003	0.008
		(0.063)	(0.062)	(0.072)
Population with diabetes (%)		−0.015	−0.025	−0.046
		(0.029)	(0.031)	(0.029)
Population with overweight (%)		0.040***	0.034**	0.035***
		(0.009)	(0.009)	(0.009)
Health expenditure in GDP (%)		0.048	0.055	0.053
		(0.037)	(0.046)	(0.049)
National median age		−0.029	−0.032	−0.033
		(0.027)	(0.034)	(0.037)
GDP per capita (in thousand $)			0.014	0.013
			(0.009)	(0.011)
Government effectiveness			−0.092	−0.132
			(0.236)	(0.265)
Mortality rate from recent pandemics				0.0004
				(0.0004)
COVID-19 tests per million				0.000003
				(0.000004)
Constant	0.148	−0.254	−0.031	−0.146
	(0.671)	(0.730)	(1.025)	(1.065)
Observations	159	138	137	129
R^2	0.615	0.687	0.697	0.701
Five continent fixed-effects	Yes	Yes	Yes	Yes

Notes: Unit of analysis is country. Robust standard errors clustered by subcontinents in parenthesis.
***$p<.001$.
**$p<.01$.
*$p<.05$.

Table A7 Results on Long-Run Efficacy of Early Mandate Adoption on Infection Rate

	(1)		(2)	
	Random-Effects Model		Fixed-Effects Model	
	Total Cumulative Infections per Million			
Mask mandates never	450.639	(288.562)	No within-group variation	
Mask mandates within 14 days	−1,409.545*	(627.084)	−1,634.176*	(665.906)
Mask mandates after 14 days	947.876	(734.269)	952.819	(737.152)
International travel bans never	435.329+	(264.011)	No within-group variation	
International travel bans within 14 days	−133.358	(441.218)	−107.065	(456.341)
International travel bans after 14 days	696.492+	(385.978)	695.830+	(386.544)
Domestic lockdowns never	107.345	(166.718)	No within-group variation	
Domestic lockdowns within 14 days	−140.208	(433.552)	−169.251	(450.400)
Domestic lockdowns after 14 days	102.731	(690.201)	99.142	(688.906)
Mass gathering bans never	524.763*	(228.039)	No within-group variation	
Mass gathering bans within 14 days	−326.066	(339.996)	−352.740	(353.241)
Mass gathering bans after 14 days	1,030.729	(632.051)	1,032.401	(633.230)
School closures never	446.685	(327.697)	No within-group variation	
School closures within 14 days	1,036.503*	(412.865)	1,088.369*	(420.240)
School closures after 14 days	−524.324	(433.207)	−532.456	(434.364)
Restaurant closures never	−378.169+	(202.927)	No within-group variation	
Restaurant closures within 14 days	−288.681	(364.086)	−300.363	(369.177)
Restaurant closures after 14 days	852.928	(988.950)	856.678	(990.848)
Partial mask mandates ever	−9.883	(141.743)	No within-group variation	
Partial international travel bans ever	−49.848	(251.809)	No within-group variation	
Partial domestic lockdowns ever	−14.582	(211.440)	No within-group variation	
Partial mass gathering bans ever	−215.325	(208.877)	No within-group variation	
Partial school closures ever	−89.565	(138.657)	No within-group variation	
Partial restaurant closures ever	374.098*	(163.795)	No within-group variation	
Constant	−615.478**	(222.652)	−199.164	(153.238)
Observations	24,684		24,684	
Within R^2	0.183		0.183	
Between R^2	0.117		0.061	
Overall R^2	0.160		0.124	
Number of countries	164		164	

Notes: Unit of analysis are country-day pairs. Random-effects generalized least squares regression used for column (1). Fixed-effects (within) regression used for column (2). Robust standard errors clustered by subcontinents in both models.

**$p < .01$.

*$p < .05$.

+$p < .10$.

Table A8 Results on Long-Run Efficacy of Early Mandate Adoption on Mortality Rate

	(1) Random-Effects Model		(2) Fixed-Effects Model	
	Total Cumulative ***Deaths*** per Million			
Mask mandates never	11.129+	(5.679)	No within-group variation	
Mask mandates within 14 days	−24.534	(51.611)	−25.608	(55.352)
Mask mandates after 14 days	−28.945+	(16.043)	−29.084+	(16.047)
International travel bans never	22.903*	(10.354)	No within-group variation	
International travel bans within 14 days	14.720	(14.506)	15.624	(15.193)
International travel bans after 14 days	52.881+	(30.172)	52.891+	(30.189)
Domestic lockdowns never	15.776+	(8.428)	No within-group variation	
Domestic lockdowns within 14 days	35.920***	(10.820)	36.435**	(11.183)
Domestic lockdowns after 14 days	50.784	(32.597)	50.703	(32.549)
Mass gathering bans never	13.911	(13.412)	No within-group variation	
Mass gathering bans within 14 days	3.393	(23.105)	3.228	(23.888)
Mass gathering bans after 14 days	45.939	(45.655)	45.945	(45.714)
School closures never	0.128	(22.696)	No within-group variation	
School closures within 14 days	8.229	(22.578)	8.607	(23.239)
School closures after 14 days	14.447	(21.831)	14.428	(21.898)
Restaurant closures never	−14.171	(10.586)	No within-group variation	
Restaurant closures within 14 days	−24.502	(18.847)	−25.232	(19.338)
Restaurant closures after 14 days	−11.978	(58.876)	−11.958	(58.920)
Partial mask mandates ever	6.283	(7.762)	No within-group variation	
Partial international travel bans ever	−7.948	(14.897)	No within-group variation	
Partial domestic lockdowns ever	4.165	(12.839)	No within-group variation	
Partial mass gathering bans ever	−4.415	(8.849)	No within-group variation	
Partial school closures ever	3.617	(5.119)	No within-group variation	
Partial restaurant closures ever	17.834+	(9.645)	No within-group variation	
Constant	−25.886**	(8.883)	−3.372	(12.843)
Observations	24,684		24,684	
Within R^2	0.178		0.178	
Between R^2	0.153		0.110	
Overall R^2	0.170		0.146	
Number of countries	164		164	

Notes: Unit of analysis are country-day pairs. Random-effects generalized least squares regression used for column (1). Fixed-effects (within) regression used for column (2). Robust standard errors clustered by subcontinents in both models.
***$p<.001$.
**$p<.01$.
*$p<.05$.
+$p<.10$.

Appendix B

Table B1 Correlation Matrix for Long-Term Analysis (Cross-Sectional, *n* = 129 in Figure 4)

	Var1	Var2	Var3	Var4	Var5	Var6	Var7	Var8	Var9	Var10	Var11	Var12	Var13	Var14
Var2	0.08													
Var3	0.03	0.35												
Var4	−0.02	0.60	0.35											
Var5	0.14	0.60	0.44	0.64										
Var6	0.12	0.59	0.43	0.69	0.54									
Var7	−0.01	−0.22	−0.05	−0.16	−0.27	−0.18								
Var8	−0.05	−0.18	−0.14	−0.15	−0.09	−0.15	0.00							
Var9	0.09	−0.34	−0.08	−0.21	−0.14	−0.20	0.39	0.36						
Var10	0.02	−0.30	−0.09	−0.22	−0.25	−0.19	0.31	−0.10	0.47					
Var11	0.00	−0.45	−0.18	−0.38	−0.42	−0.35	0.71	0.21	0.67	0.47				
Var12	−0.03	−0.47	−0.15	−0.42	−0.40	−0.34	0.34	0.31	0.53	0.28	0.61			
Var13	−0.11	−0.47	−0.23	−0.38	−0.51	−0.39	0.47	0.22	0.53	0.45	0.77	0.78		
Var14	−0.01	0.10	0.03	0.10	0.08	0.04	−0.08	−0.12	−0.10	0.06	−0.13	−0.09	−0.15	
Var15	−0.02	−0.24	0.01	−0.20	−0.18	−0.20	0.24	0.26	0.44	0.09	0.41	0.61	0.50	−0.07

Notes: Var1: early mask mandate; Var2: early international travel bans; Var3: early domestic lockdowns; Var4: early mass gathering bans; Var5: early school closures; Var6: early restaurant closures; Var7: hospital beds per 1,000 population; Var8: population with diabetes (%); Var9: overweighed population (%); Var10: health expenditure in GDP (%); Var11: national median age; Var12: GDP per capita (in $1000); Var13: government effectiveness; Var14: mortality rate from three recent pandemics (Ebola, H1N1, SARS); Var15: COVID-19 tests per million (averaged between 90th and 120th days since first case). All early mandates were coded in three scales (0: no adoption; 0.5: partial adoption; and 1: strict adoption). The model also included whether each mandate was adopted ever during the study period, but not shown here for space constraint.

Table B2 Correlation Matrix for Short-Term Analysis (Longitudinal, *n* = 21,155 in Figure 3)

	Var1	Var2	Var3	Var4	Var5	Var6	Var7	Var8	Var9
Var2	−0.16								
Var3	−0.15	0.61							
Var4	−0.57	0.24	0.17						
Var5	−0.27	0.08	−0.07	0.40					
Var6	−0.20	−0.03	−0.03	0.25	0.16				
Var7	0.03	−0.05	−0.03	−0.09	−0.07	0.21			
Var8	−0.21	0.04	0.06	0.30	0.17	0.32	0.15		
Var9	−0.02	−0.02	0.03	−0.04	−0.04	0.22	0.41	0.35	
Var10	−0.15	0.02	−0.01	0.26	0.22	0.33	0.34	0.38	0.36

Notes: Var1: Rate of new cases; Var2: Cumulative cases; Var3: Cumulative deaths; Var4: Days since January 1, 2020 (logged); Var5: Strict mask mandates; Var6: Strict international travel restrictions; Var7: Strict domestic lockdowns; Var8: Strict mass gatherings bans; Var9: Strict restaurants closures; Var10: Strict schools closures. While the variables for six mandate measures in Table A1 were lagged with five different timeframes, those presented in the correlation matrix are not lagged. Still, they effectively capture the bivariate relationships among the policy measures. A mandate's evolution over time—being lifted and re-imposed during the study period—is still captured by the correlation matrix.

Table B3 Correlation Matrix for Long-Term Analysis (Longitudinal, *n* = 24,684 in Figure 5)

	Var1	Var2	Var3	Var4	Var5	Var6	Var7	Var8	Var9	Var10	Var11	Var12	Var13	Var14	Var15	Var16	Var17
Var2	−0.10																
Var3	0.05	0.14															
Var4	0.04	0.14	−0.42														
Var5	0.05	0.10	0.38	−0.19													
Var6	0.05	0.06	−0.28	0.51	−0.25												
Var7	0.04	0.23	0.56	−0.18	0.25	−0.11											
Var8	−0.01	0.03	−0.31	0.40	−0.12	0.48	−0.42										
Var9	0.15	0.20	0.61	−0.14	0.36	−0.06	0.61	−0.19									
Var10	−0.08	0.11	−0.35	0.42	−0.18	0.33	−0.29	0.46	−0.57								
Var11	0.08	0.18	0.52	−0.19	0.43	−0.14	0.58	−0.31	0.51	−0.26							
Var12	−0.01	0.05	−0.26	0.41	−0.09	0.60	−0.24	0.68	−0.20	0.43	−0.32						
Var13	−0.04	−0.17	0.04	−0.03	−0.02	0.07	0.02	0.01	−0.04	0.06	0.00	0.09					
Var14	0.01	−0.10	−0.44	0.10	−0.05	0.13	−0.34	0.20	−0.31	0.17	−0.28	0.24	0.00				
Var15	−0.01	0.09	−0.04	0.01	−0.13	−0.09	−0.03	0.00	−0.07	0.10	−0.07	0.03	0.01	0.04			
Var16	−0.09	−0.01	−0.18	0.06	0.00	−0.10	−0.28	−0.06	−0.24	0.15	−0.16	−0.02	−0.01	0.14	0.10		
Var17	−0.06	−0.10	−0.13	0.10	−0.05	0.09	−0.08	0.10	−0.30	0.20	−0.11	0.13	0.22	0.16	−0.01	0.08	
Var18	−0.06	−0.06	0.01	0.04	0.01	−0.04	0.02	0.02	0.04	−0.06	−0.07	−0.03	0.07	0.00	0.10	0.15	0.03

Notes: Var1: Strict early mask mandates; Var2: Strict late mask mandates; Var3: Strict early international travel bans; Var4: Strict late international travel bans; Var5: Strict early domestic lockdowns; Var6: Strict late domestic lockdowns; Var7: Strict early mass gathering bans; Var8: Strict late mass gathering bans; Var9: Strict early school closures; Var10: Strict late school closures; Var11: Strict early restaurant closures; Var12: Strict late restaurant closures; Var13: Partial mask mandate ever; Var14: Partial international travel bans ever; Var15: Partial domestic lockdowns ever; Var16: Partial mass gathering bans ever; Var17: Partial school closures ever; Var18: Partial restaurant closures ever. The variables "(strict) mandates never" are not reported due to space constraints.